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Research Paper

Measurement of Financial Inclusion in India: An Integrated Approach with TOPSIS and EWM

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ABSTRACT

The extent of financial inclusion among Indian states for the period has been measured and compared by constructing a composite index using an integrated methodology of TOPSIS (Technique of order preference by similarity to ideal solution) with EWM (Entropy Weighting Method). The proposed index has three broad dimensions of banking penetration, availability, and usage of banking services with an extended variable. Data for the study include: state wide bank data, demographic, geographic, and economic data, and are taken from Reserve Bank of India's (RBI) publications. There is a general improvement in financial inclusion in India, while UT of Chandigarh and Delhi top the index, and Manipur and Nagaland bottom of the index. The southern region tops India on financial inclusion in terms of average rank. The methodology adopted in this study is not widely adopted in IFI literature. Moreover, the index has been constructed with statically assigned weight by using EWM.

HIGHLIGHTS

- There is a general improvement in financial inclusion in India, while UT of Chandigarh and Delhi top the index, and Manipur and Nagaland bottom of the index. The southern region tops India on financial inclusion in terms of average rank.
- The weights and factors used will affect the index results. Since the current study created an index with statistically determined weights, subjectivity is mainly eliminated.

Keywords: Financial Inclusion, Multidimensional Index, TOPSIS, EWM, Inclusive Growth

The distance between a global economy and an inclusive global economy could be better. Unprecedented progress is being made toward the objective of a diverse and inclusive global economy. According to the most recent data, between 2014 and 2017, 515 million adults globally had deposit or transaction accounts with financial institutions or mobile money providers, representing 69 percent of all individuals worldwide, an increase from 62 percent in 2014. The inclusion rate, as of right now, is rather endearing. However, about half of the 1.7 billion adults worldwide who lack access to banking services or are financially excluded—including women and poor rural households—remain unbanked or uninsured (Global Findex Report, 2017).

In India, reducing poverty is best accomplished by promoting financial inclusion. The Reserve Bank of India (RBI) required all Scheduled Commercial Banks (SCBs) to align their business practices to reach the financially excluded people in its Annual Policy Statement for 2005–2006. Despite a sizable body of literature on IFI, relatively few studies have been done on Indian states or UTs due to a lack of

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data. Furthermore, most of the research generated index of financial inclusion (IFI) using subjective weights rather than statistically determined weights. A common claim is that "the constructed index is sensitive to the weight assigned." The current study attempts to close this gap by creating an IFI for Indian states and UTs using EWM and statistically allocated weights.

Following (Yadav and Sharma, 2016), we created IFI for Indian states and union territories from 2011 to 2017. The current study, however, differs from (Yadav and Sharma, 2016) in several ways: (1) they constructed the IFI with subjective weights, whereas the constructed IFI in our study follows objective weights computed with EWM; (2) they only took into account three criteria, whereas the current study included as many as 12 criteria by adhering to the findings of (Gupte *et al*. 2012), which found that adding more and more dimensions to the index will give a complete result. (3) To test the claim made in the literature that "IFI constructed are sensitive to the weight assigned," the present study created two distinct indices based on both subjective and objective weights. (4) Their study period was only two years, whereas we created IFI for a more extended period of seven years.

The remainder of the study is structured as follows: Section 2 presents the literature review; Section 3 discusses the research methodology; Section 4 analyzes the results; and we discuss the results in Section 5. Finally, in Section 6, we conclude our study.

Literature Review

In the literature, (Sarma, 2008) is branded for creating an index of financial inclusion. She calculated two sets of IFI, one in three dimensions for 55 nations and the other in two for 100 countries. A two-dimensional index only contained (1) banking availability and (2) usage of banking services due to the lack of data for the outreach dimension, but a three-dimensional index included (1) banking penetration, (2) banking availability, and (3) utilization of banking services. The methodology (Sarma, 2008) used to create the HDI and GDI is comparable to that used by the UNDP.

For 23 Indian states in 2009, (Chattopadhyay, 2011) heterogeneity across states is widespread. Gap between rural and urban areas in respect of outreach is also prevalent even after the reform period. While significant improvement has taken place in credit/loan account in the urban households, the situation has become worse for the rural households. An index of financial inclusion (IFI created an IFI with three dimensions, followed by (Sarma, 2008) and discovered that Maharashtra topped the index with an IFI value of 0.558, followed by Karnataka, while Nagaland and Manipur received the lowest scores. In their investigation, (Pal and Vaidya, 2011) calculated IFI values for 1981, 1991, 1996, 2001, and 2007. They discovered that the UTs of Delhi, Goa, and Kerala exhibit consistent performance and keep the top three spots, respectively. In contrast, Manipur holds onto the worst spot throughout the study.

The financial inclusion index was calculated for 82 nations for the year 2011 utilizing usage, barrier, and access dimensions with statistically assigned weights using two-stage PCA (Cámara *et al*. 2014). On the index created using data from both the supply and demand sides, they discovered that Korea is the top-performing nation. Perhaps (Cámara *et al.* 2014) are the first to use PCA in IFI literature.

The UNDP methodology used to construct the HDI in 2010 was used by (Gupte *et al*. 2012) to construct the index for three consecutive years, 2008, 2009, and 2010. They found an increase in financial inclusion from 2008 to 2009 by using the dimensions of ease and cost of transactions in addition to outreach (penetration and accessibility) and usage. They have incorporated as many as possible with the justification that more indicators produce a complete result. In the IFI literature, (Gupte *et al*. 2012) may be the first to introduce the most significant number of indicators. (Yorulmaz, 2018) proposed two distinct IFI indices. The first is constructed for 179 countries from 2004 to 2011 and considers three dimensions: reach, use, and ease of transactions. It was discovered that Singapore and Luxembourg held the first and second positions, respectively, and did so in both 2004 and 2011.

By using the TOPSIS methodology and the dimensions from (Sarma, 2008; Yadav and Sharma, 2016) created an index of financial inclusion for Indian states and UTs. They discovered that Chandigarh, Delhi, Goa, and Maharashtra maintain

Table 1: Dimensions and Performance Measures Used in the Empirical Model

Dimensions	Performance Measures
D1: Availability	**P1:** No. of bank offices available/1000 population. **P2:** No. of bank offices available/1000 sq.km. **P3:** No. of bank employees/1000 customers. **P4:** No. of rural offices/1000 rural population.
D2: Outreach	**P5:** No. of deposits and credit accounts/1000 population. **P6:** No. of rural deposits and credit accounts/1000 rural population. **P7:** No. of female deposit accounts/1000 female population. **P8:** No. of agricultural account/1000 rural population.
D3: Usage	**P9:** Proportion of volume of deposit and credit to SGDP. **P10:** Proportion of outstanding volume of rural deposit and credit to SGDP. **P11:** Proportion of volume of female deposit to SGDP. **P12:** Proportion of volume of agricultural credit to sectoral GDP of agriculture.

Source: *Prepared by the author.*

their top four positions in both years, while Bihar and Manipur are the worst-performing states. (Goel and Sharma, 2017) built an IFI with three dimensions of availability, penetration, and usage across twelve years (2005–12), and they discovered that India had poor financial inclusion during the research period. For India, (Sethy, 2016) created two distinct indices for supply-side indicators (1975–2012) and demand-side indicators (2004–12) and discovered that Chandigarh and the UT of Delhi perform the best in both indices, followed by Maharashtra and Goa.

Research Methodology

The present study constructed a multi-dimensional index by using an integrated approach of TOPSIS and EWM to measure financial inclusion among Indian states for the period of 2011–2017 and rank the states based on IFI scores. We followed (Sarma, 2008) and created IFI with three dimensions: (1) banking outreach, (2) availability, and (3) consumption of financial services, with 12 variables in total. A description of the performance measures used in the present study is given in table 1.

State-wide bank-related data have been collected from "Basic Statistical Returns of Scheduled Commercial Banks" published by the Reserve Bank of India (RBI) annually from 2011 to 2017. All the demographic, geographic, and economic variables used for this study have been taken from "The Handbook of Statics on the Indian States," an annual publication by RBI. The sample size of the study includes 32 Indian states and union territories[1].

We used EWM to compute the weights of the performance measures used in the study. We used TOPSIS to find IFI values and rank the states and union territories. We provide a reasonable explanation of EWM and TOPSIS in the following paragraphs.

(a) Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS)

An essential and widely used Multi-Criteria Decision (MCDM) method called TOPSIS was first created by (Hwang & Yoon, 1981) maximin and maximum which are still fit for the MADM environment. They do not require the DM's preference information, and accordingly yield the objective (vs. subjective. The "Euclidean distance approach" underlies TOPSIS, which states that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the longest distance from the negative ideal solution (NIS) (Bhanot and Bapat, 2016; Firmialy and Nainggolan, 2019; Salmeron *et al.* 2012; Tang *et al.* 2019; Tsou, 2008).

If ratings for each alternative against several criteria are available, TOPSIS ranks M alternatives based on N criteria (Bhanot *et al.* 2015). In this

[1]UT of Dadra & Nagar Haveli, Daman & Diu, Lakshadweep are excluded from the study as data on GDP is not available, though bank related data are available. June 2, 2014 onwards, Telangana is a separate state, but Telangana is treated as a part of Andhra Pradesh throughout the study.

study, the number of states and UTs to be ranked and evaluated (M) is 32, and the number of criteria reviewed against states and UTs (N) is 12. The following paragraph provides a detailed explanation of the step-by-step process for building IFI using TOPSIS.

***Step 1. Construction of Normalized M×N Decision Matrix**:* TOPSIS methodology begins with the normalization of raw data to form a normalised M × N decision matrix, which allows comparisons across the criteria. Normalisation is done with the following formulae:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{M}\left(x_{ij}\right)^2}}$$

where, x_{ij} (i € M; j € N) represents each element of the M×N matrix.

***Step 2. Construction of Weighted Normalized M×N Decision Matrix**:* Relative weights are assigned for each criterion. It can be done subjectively or objectively, the present study assigned weights objectively with EWM. This matrix can be built with the following formulae.

$$V_{ij} = w_j * r_{ij}$$

where, w_j represents weight assigned to each criterion and r_{ij} represents the normalised x_{ij} values.

***Step 3. Computation of Positive & Negative ideal solutions**:* As TOPSIS ranks alternatives based on the positive ideal and negative ideal solution, each criterion is either maximised or minimised to obtain the best alternative known as positive ideal (A*) and worst alternative known as negative ideal (A-). Generally, the beneficial criterion is maximised, and the non-beneficial criterion is minimised to find the positive ideal and vice versa for the negative ideal. A* and A- defined as;

$$\boldsymbol{A^*} = \begin{cases} \left(\begin{matrix}\max \\ j\end{matrix}\right) v_{ij} & \forall\, i \text{ when criteria } j \text{ is to be maximized} \\ \left(\begin{matrix}min \\ j\end{matrix}\right) v_{ij} & \forall\, i \text{ when criteria } j \text{ is to be minimized}\end{cases} = v_1^*, v_2^*, v_3^*$$

$$\boldsymbol{A^-} = \begin{cases} \left(\begin{matrix}\min \\ j\end{matrix}\right) v_{ij} & \forall\, i \text{ when criteria } j \text{ is to be maximized} \\ \left(\begin{matrix}max \\ j\end{matrix}\right) v_{ij} & \forall\, i \text{ when criteria } j \text{ is to be minimized}\end{cases} = v_{1-}, v_{2-}, v_{-3}$$

Step 4. Calculation of Separation Measure (Distance): The next step is to compute a separation measure/distance for each M from the positive ideal, s_i*, and negative ideal, $\bar{s}_i$, and would be calculated as:

$$\boldsymbol{s_i^*} = \sqrt{\textstyle\sum_{j=1}^{3}\left(\boldsymbol{v_{ij-}}\ \boldsymbol{v_j^*}\right)} \quad \text{for } i = 1,2,3\ldots., 32.$$

$$\boldsymbol{s_i^-} = \sqrt{\textstyle\sum_{j=1}^{3}\left(\boldsymbol{v_{ij-}}\ \boldsymbol{v_j^-}\right)}, \text{ for } i = 1,2,3\ldots.,32.$$

Step 5. Computation of relative closeness to the ideal solution: Relative closeness to the ideal solution for each M is computed as follows, and the value ranges between 0 and 1, where a higher value indicates better performance;

$$\boldsymbol{c_i^*} = \frac{S_{i-}}{S_{i*} + S_{i-}}$$

Step 6. Rank the Alternatives: Finally, ranks are assigned to each alternative in descending order based on their relative closeness to the ideal solution.

(b) ***Entropy Weight Method (EWM)***

The objective weighing approach described by the Entropy Weighting Method (EWM) can be reduced and even eradicated. The EWM is suitable for differentiating the alternatives due to its intrinsic sensitivity to its indicators' diversity or information entropy (Chen, 2019)which are widely used in risk assessment and decision-making for natural hazards. However, for the attributes with a specific range of values (RV. As a result, the current study computed weights objectively using the entropy approach using the following stages and the methods described in (Aras *et al*. 2017; Li *et al*. 2014; Liu and Zhang, 2011). The weights are shown in table 2.

With m indicators and n samples in the data set to evaluate the weights, the value measured can be denoted as x_{ij}. The decision matrix, $\{r_{ij}\}$, can be developed by standardizing the values measured (Aras *et al*. 2017; Ding *et al*. 2017; Dong *et al*. 2010). The formula for the standardisation is as follows:

$$r_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}$$

The calculation of the entropy value, e_i of the indicators is as follows:

$$e_i = \frac{\sum_{j=1}^{n} r_{ij} \ln r_{ij}}{-\ln n}$$

The entropy value ranges between 0 and 1. The entropy value can also be called the degree of differentiation. The greater the entropy value is, the larger the degree of differentiation of the indicator. The calculation of the weights by entropy weighting method is:

$$w_i = \frac{1 - e_i}{\sum_{i=1}^{m} (1 - e_i)}$$

RESULTS ANALYSIS

We have constructed an index of financial inclusion for Indian states by following an integrated approach of TOPSIS and EWM for 2011–2017. Table 2 exhibits the weights assigned to the performance measures used in the study based on the entropy method. The most important of the twelve performance measures is the ratio of the volume of agricultural loans to the sectoral agricultural GDP (P12), followed by the number of bank employees per thousand customers (P3). These two performance indicators receive over 60% of the total weight. In order to compare the outcomes of our index, we also created a second index using the TOPSIS approach with subjective weights (weights are assigned based on previous studies, precisely 40% for D1, 30% each for D2 and D3).

The descriptive statistics of financial inclusion across Indian states over the study period are given in tables 3 and 4. The results provide evidence for increased levels of financial inclusion in India. The average IFI values over the years have been increasing, particularly since 2013. The average level of financial inclusion in India throughout the study, as measured by our index, ranges from 0.067 to 0.074, whereas it ranges from 0.151 to 0.182 based on the second index specifically. Hence, financial inclusion, as measured by an index with subjective weights, exhibits inflated performance compared to an index with statistically assigned weights.

Chandigarh marked the highest financial inclusion throughout the study period, followed by Delhi. Comparing their individual IFI scores reveals significant performance differences in financial inclusion between the two union territories. However, after 2013, this variation became less noticeable as the UT of Chandigarh exhibited lower performance than the UT of Delhi (Appendix A). Therefore, Chandigarh may eventually lose to UT of Delhi, but only sometime soon.

In addition to Chandigarh, seven other states—Goa, Andhra Pradesh, Karnataka, Sikkim, Maharashtra, Andaman and Nicobar Island, and Gujarat—exhibited a deteriorating performance in terms

Table 2: Computed weights of Performance Measures using Entropy Method

	2011	2012	2013	2014	2015	2016	2017
P1	0.004	0.006	0.007	0.007	0.008	0.009	0.009
P2	0.023	0.022	0.023	0.023	0.024	0.024	0.024
P3	0.263	0.248	0.265	0.274	0.285	0.304	0.305
P4	0.085	0.078	0.050	0.052	0.058	0.054	0.054
P5	0.023	0.020	0.020	0.019	0.017	0.014	0.014
P6	0.092	0.080	0.047	0.048	0.048	0.038	0.038
P7	0.035	0.031	0.033	0.029	0.026	0.019	0.019
P8	0.065	0.059	0.061	0.070	0.072	0.074	0.074
P9	0.032	0.030	0.031	0.031	0.031	0.026	0.026
P10	0.019	0.017	0.023	0.026	0.028	0.035	0.033
P11	0.018	0.018	0.017	0.019	0.019	0.016	0.016
P12	0.340	0.391	0.423	0.402	0.385	0.387	0.388

Source: *RBI Database,* ***Note:*** *Values Computed.*

Table 3: Descriptive Statistics of IFI values of States/UTs

Year	Range	Min.	Max.	Mean	SD
2011	0.978	0.003	0.981	0.067	0.176
2012	0.985	0.002	0.988	0.061	0.176
2013	0.975	0.003	0.978	0.060	0.174
2014	0.972	0.004	0.976	0.064	0.175
2015	0.957	0.004	0.960	0.068	0.176
2016	0.942	0.005	0.947	0.074	0.182
2017	0.931	0.006	0.937	0.074	0.181

Source: *RBI Database;* ***Note:*** *Values Computed by the author, represents TOPSIS with EWM.*

Table 4: Descriptive Statistics of IFI values of States/UTs

Year	Range	Min.	Max.	Mean	SD
2011	0.857	0.023	0.881	0.151	0.156
2012	0.878	0.021	0.899	0.157	0.159
2013	0.798	0.028	0.826	0.171	0.153
2014	0.796	0.028	0.824	0.173	0.153
2015	0.795	0.020	0.816	0.172	0.153
2016	0.753	0.046	0.799	0.180	0.149
2017	0.704	0.055	0.759	0.182	0.143

Source: *RBI Database;* ***Note:*** *Values Computed by the author.*

of financial inclusion (see change in IFI values in appendix A). In the beginning, Puducherry was in fourth place. The union territory has advanced since 2014, surpassing Goa. Tripura improved their ranking significantly, from twenty second position to tenth position by the end of 2017. Similarly, Meghalaya, West Bengal, and Assam also improved their position over a period of time (see change in rank in appendix B).

Northern region states exhibited higher financial inclusion, particularly both Chandigarh and Delhi, holding first and second positions belonging to this region. Among the northern regions, Rajasthan has the lowest level of financial inclusion, followed by Jammu, Kashmir, and Haryana. Southern region states perform relatively well in their ranks based on computed IFI values. However, the IFI values against the two top performers in the country are minimal. Puducherry has the highest financial inclusion in the southern region, and Karnataka has the lowest. North-eastern states (Manipur, Meghalaya, Assam, and Arunachal Pradesh) are the least inclusive of Indian states in terms of financial inclusion.

DISCUSSION

This research has taken a multi-dimensional approach to the concept of financial inclusion. Since 2011, financial inclusion has been measured in several Indian states and union territories (UTs). We used two multi-criterion decision-making models (EWM and TOPSIS) to construct the financial inclusion index. Ours is the first study to use the entropy weight method to statistically assign weight to the performance measures used in the model. Further, we are the first to combine EWM with TOPSIS to construct a financial inclusion index. Yadav and Sharma (2016) used TOPSIS in their study, but they have yet to use any scientific method to fix the weights of performance measures. Hence, we have adopted EWM to fix the parameter weights and TOPSIS to measure the financial inclusion among Indian states and to rank the states based on performance.

Yadav and Sharma (2016) is the benchmarking study used in the present study. We have replicated their index in the present study by assigning parameter weights subjectively (40% for D1, 30% for D2, and 30% for D3). However, our second index partially replicates Yadav and Sharma's (2016) because we constructed it with an extended set of performance measures. The two significant performance measures identified by our entropy method are (1) the ratio of the volume of agricultural loans to the sectoral agricultural GDP and (2) the number of bank employees per thousand customers. Yadav and Sharma (2016) assigned 30 percent weight to the performance measure "the number of bank employees per thousand customers." Similarly, our entropy method assigned almost the same weights to this performance measure. In contrast, our index gave only 3 percent and 0.4 percent to the other two measures used by Yadav and Sharma (2016).

The top two cities in the financial inclusion index throughout the study were Chandigarh and Delhi. This result reaffirms the results of Yadav and Sharma (2016). Further, comparing the respective rankings of states and UTs derived from the present study reveals that the degree of financial inclusion in India has increased by an average of 0.04 points since 2014. Comparing the descriptive statistics of the two indices built in the current study showed that the performance of the index with subjective weights, which measures financial inclusion, is overstated compared to the index with statistically assigned weights. Chandigarh, Delhi, Puducherry, and Goa have high levels of financial inclusion, whereas other Indian states in the analysis had low levels of financial inclusion. Over the period, only a few states had an improvement in their ranking on the index, while others saw a decline. States in the northern and southern regions are more inclusive in terms of financial inclusion than states in the northeast.

CONCLUSION, LIMITATIONS, AND FUTURE SCOPE OF THE STUDY

Having a deposit or transaction account at a bank or other financial institution is the first step in achieving financial inclusion. However, much more is needed to create an inclusive financial system. Reaching out to vulnerable groups like women, weaker groups, and those with low incomes entails ensuring they have access to financial services and timely loans. As a result, any attempt to quantify financial inclusion should be multifaceted and include all metrics that capture its full extent. If not, measurement only provides incomplete and biased information.

The study's conclusions show that financial inclusion in India has generally improved. The UTs of Chandigarh and Delhi consistently rank at the top of the ranking, whereas Manipur and Nagaland consistently come last. In terms of mean ranks, the Southern Region came out on top in 2011 and 2017. The weights will impact the index results and other parameters utilized. The present study will benefit researchers and policymakers by evaluating the current state of financial inclusion and the effectiveness of the various financial policies implemented by the national and state governments to encourage financial inclusion in India. However, the study faces the following limitations: (1) the scope of the study is limited to banking institutions; thus, it excluded other institutions; and (2) due to the unavailability of data, it omitted some significant dimensions such as ease and cost of transactions.

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Appendix A

IFI Values of States/UTs with Objective Weight by using Entropy Method

State	2011	2012	2013	2014	2015	2016	2017	Change in IFI
Chandigarh	0.981	0.988	0.978	0.976	0.960	0.947	0.937	-0.044
Delhi	0.317	0.268	0.261	0.314	0.374	0.510	0.517	0.199
Goa	0.103	0.088	0.084	0.087	0.089	0.080	0.091	-0.012
Puducherry	0.096	0.084	0.084	0.096	0.113	0.121	0.129	0.033
Tamil Nadu	0.059	0.050	0.046	0.053	0.061	0.062	0.065	0.005
Kerala	0.050	0.040	0.040	0.044	0.059	0.057	0.055	0.005
Andhra Pradesh	0.044	0.037	0.034	0.037	0.040	0.039	0.037	-0.006
Himachal Pradesh	0.041	0.034	0.034	0.036	0.038	0.043	0.046	0.005
Karnataka	0.034	0.026	0.026	0.028	0.030	0.031	0.030	-0.004
Punjab	0.033	0.028	0.029	0.032	0.035	0.038	0.041	0.008
Uttarakhand	0.027	0.022	0.021	0.022	0.023	0.025	0.027	0.000
Sikkim	0.026	0.023	0.024	0.027	0.028	0.027	0.025	-0.001
Maharashtra	0.025	0.021	0.021	0.022	0.023	0.022	0.022	-0.003
Haryana	0.024	0.020	0.020	0.022	0.024	0.026	0.027	0.003
Andaman & Nicobar Islands	0.022	0.021	0.021	0.022	0.022	0.024	0.021	-0.001
Jammu & Kashmir	0.022	0.019	0.020	0.023	0.027	0.026	0.026	0.004
Mizoram	0.021	0.020	0.020	0.023	0.022	0.020	0.021	0.000
Odisha	0.019	0.015	0.015	0.016	0.018	0.021	0.020	0.001
Uttar Pradesh	0.019	0.016	0.015	0.017	0.018	0.021	0.022	0.003
Gujarat	0.018	0.015	0.014	0.016	0.015	0.016	0.017	-0.001
West Bengal	0.018	0.016	0.016	0.018	0.019	0.023	0.024	0.006
Tripura	0.018	0.017	0.018	0.021	0.021	0.035	0.031	0.014
Arunachal Pradesh	0.015	0.012	0.012	0.014	0.012	0.016	0.016	0.002
Bihar	0.014	0.012	0.013	0.015	0.017	0.022	0.020	0.006
Rajasthan	0.014	0.011	0.010	0.011	0.012	0.015	0.016	0.001
Meghalaya	0.014	0.011	0.012	0.014	0.015	0.019	0.022	0.008
Jharkhand	0.013	0.011	0.011	0.014	0.014	0.018	0.019	0.005
Madhya Pradesh	0.012	0.010	0.009	0.011	0.011	0.012	0.013	0.001
Assam	0.011	0.009	0.009	0.010	0.011	0.016	0.017	0.007
Chhattisgarh	0.010	0.008	0.008	0.009	0.009	0.011	0.012	0.002
Nagaland	0.005	0.005	0.005	0.004	0.004	0.005	0.006	0.001
Manipur	0.003	0.002	0.003	0.004	0.004	0.008	0.009	0.006

Source: *RBI Database;* ***Note:*** *Values Computed.*

Appendix B

Rank of States/UTs on IFI value with Entropy Weight

Region / State /UT	2011	2012	2013	2014	2015	2016	2017	Change in Rank
Chandigarh	1	1	1	1	1	1	1	0
Delhi	2	2	2	2	2	2	2	0
Goa	3	3	3	4	4	4	4	-1
Puducherry	4	4	4	3	3	3	3	1
Tamil Nadu	5	5	5	5	5	5	5	0
Kerala	6	6	6	6	6	6	6	0
Andhra Pradesh	7	7	7	7	7	8	9	-2
Himachal Pradesh	8	8	8	8	8	7	7	1
Karnataka	9	10	10	10	10	11	11	-2
Punjab	10	9	9	9	9	9	8	2
Uttarakhand	11	12	13	14	14	15	12	-1
Sikkim	12	11	11	11	11	12	15	-3
Maharashtra	13	13	14	16	15	18	18	-5
Haryana	14	16	17	17	13	13	13	1
Andaman & Nicobar Islands	15	14	12	15	17	16	21	-6
Jammu & Kashmir	16	17	15	13	12	14	14	2
Mizoram	17	15	16	12	16	22	20	-3
Odisha	18	21	21	21	21	21	23	-5
Uttar Pradesh	19	20	20	20	20	20	17	2
Gujarat	20	22	22	22	23	26	26	-6
West Bengal	21	19	19	19	19	17	16	5
Tripura	22	18	18	18	18	10	10	12
Arunachal Pradesh	23	24	24	26	26	25	27	-4
Bihar	24	23	23	23	22	19	22	2
Rajasthan	25	26	27	27	27	28	28	-3
Meghalaya	26	25	25	24	24	23	19	7
Jharkhand	27	27	26	25	25	24	24	-3
Madhya Pradesh	28	28	28	28	28	29	29	-1
Assam	29	29	29	29	29	27	25	4
Chhattisgarh	30	30	30	30	30	30	30	0
Nagaland	31	31	31	31	31	32	32	-1
Manipur	32	32	32	32	32	31	31	1

Source: *RBI Database;* ***Note:*** *Values Computed.*