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MEASUREMENT OF FINANCIAL INCLUSION: A COMPARISON OF SELECTED METHODOLOGIES

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Abstract:- Purpose: The aim is to compare the selected methodologies used for constructing an Index of Financial Inclusion (IFI), as there exists conflict over the methodologies adopted to construct a financial inclusion index in the literature in terms of performance accuracy, and efficiency. The impact of dimension weights on index values has also been studied. **Design/methodology/approach:** An IFI has been built with three broad dimensions, banking penetration, availability, and usage of banking services with the selected methodologies. Data for the study include state/UT-wide bank data, demographical, geographical, and economic data, which are taken from Reserve Bank of India's publications**. Findings:** (1) An IFI constructed with the methodologies (TOPSIS with EWM and Sarma (2015) with EWM) shows almost similar performances in terms of descriptive statistics; (2) There is only a slight difference in the financial inclusion performance between the methodologies based on Camera and Tuesta (2014) with two-stage PCA and Sarma (2008, 2015) with the subjective weights which make use of the descriptive statistics; (3) Camera and Tuesta (2014) methodology assigns a narrow weight to the index dimensions whereas, the proposed two-stage PCA model assigns a wider weight. **Practical implications:** The present study is useful to all the stakeholders, who are interested in the measurement of financial inclusion, say policymakers, research communities, etc., and the study offers direction to future studies on the methodology to be adopted. **Originality/value –** To the best of authors' knowledge, no studies have been carried out with the same purpose. Hence, the present study is new to the IFI literature.

Keywords: Financial Inclusion Index, Two-stage PCA, TOPSIS, EWM, Inclusive Growth

Introduction:

The term "financial inclusion" describes initiatives to make financial products and services available and cheap to all people and businesses, regardless of their personal net worth or the size of their organisation. The goal of financial inclusion is to overcome the obstacles that prevent people from engaging with the financial system and utilising its products to better their lives. Financial inclusion ensures that everyone in an economy may easily access, use, and be a part of the formal financial system. There are several advantages to an inclusive financial system. As a result, it may help to lower the cost of capital by facilitating the effective deployment of productive resources. The handling of funds on a daily basis can also be greatly improved by having access to the right financial services. Therefore, an all-encompassing financial system improves efficiency and welfare by facilitating a wide range of effective financial services as well as avenues for safe and secure saving activities.

A number of initiatives were put forward to promote financial inclusion across the economies, mainly by the central bank of the respective economies. Initiatives by IMF, G20, International Finance Corporation (IFC), the Alliance for Financial Inclusion (AFI), and the Consultative Group to Assist the Poor (CGAP) plays major role globally in data accumulation and standard setting process to improve financial inclusion.

The index of financial inclusion (IFI) measures a country's financial sector's inclusiveness. It is a multidimensional indicator that measures financial inclusion factors like banking penetration, availability, and usage. The IFI uses one number between 0 and 1 to represent these dimensions, where 0 is complete financial exclusion and 1 is complete financial inclusion in an economy.

Sarma (2008, 2012, 2015), Principal Component Analysis (PCA) and Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) are the major and widely used methodologies in the IFI. The study has been carried out on the background that, there exists conflict over the methodologies (Camara & Tuesta, 2014; Chakravarty & Pal, 2010; Gupte et al., 2012; Sarma, 2008, 2012, 2015; Yadav & Sharma, 2016) adopted to construct financial inclusion index in the literature in terms of performance accuracy, and efficiency. Sarma (2008) is the first study which quantifies the level of financial inclusion of various economies by building a multidimensional index, popularly called as index of financial inclusion (IFI). Most of the studies in the IFI literature adopted Sarma (2008) methodology to construct IFI in later years. But some studies proposed new methodologies by criticizing Sarma (2008) methodology. One of such prominent studies is Camera and Tuesta (2014), which proposes the two-stage PCA methodology by claiming that 'IFI are sensitive to the dimensional weight assigned, and Sarma (2008) index assigned dimension weights subjectively, hence that index will not provide true results. In 2016, Yadav and Sarma proposed TOPSIS methodology and computed IFI for Indian states for the year 2011 and 2014, they have also assigned weights subjectively. In 2015, Sarma computed an improved index by following a "distance-based approach" by claiming that the new index will overcome the limitations of Sarma (2008) index.

Rationale/ Significance of the Study:

The present state of financial inclusion across the economies needs to be measured of variety of reasons, hence, a robust and complete measure of financial inclusion is highly desired. Such a measure is important to the policymakers to account the improvement of policy initiatives implemented to enhance financial inclusion across the economies and to compare the results in terms of relative performance. It can also be beneficial to the academic and research communities to test different hypothesis in the financial inclusion literature (Sarma, 2008). Hence, a good number of attempts has been made so far to build such a complete measure of financial inclusion, but it can be observed that, there is no consensus in the methodologies adopted. This study compares the findings of multiple approaches used to develop a multi-dimensional index to evaluate financial inclusion across economies.

Objectives:

The objectives of this study can be classified into two paradigms.

I. To analyse the different methodologies adopted to build a complete measure of financial inclusion from the literature.
II. To construct an index of financial inclusion among Indian states/UTs with identified methodologies and to compare the results.

Review of Literature:

Measurement of financial inclusion is a major focus of the financial inclusion literature, and are in good number. The present study has reviewd some of the prominent studies; (Beck et al.,2006; Honohan,2008; Sarma,2008,2012,2015; Chattopadhyay,2011; Arora,2014; Sethy,2016; Goel and Sharma,2017a; Gupte et al.,2012; Yorulmaz,2018; Wang and Guan,2017; Bozkurt et al.,2018; Chakravarty and Pal,2010; Camera and Tuesta,2014; Yadav and Sharma,2016; Raichoudhury,2016; and Le et al.,2019). The major focus of this review is on: (a) methodologies adopted; and (2) dimensions/ indicators included in the IFI literature. Main observations of the author on these dimensions are presented in **Table I** and **Table II**.

Beck et al. (2006), considered to be the first attempt to measure the outreach of financial inclusion across the economies followed by Honohan (2008), who accounted the percentage of househlods/adults access to financial services for 160 countries. However, Honohan's (2008) findings are questioned with the claim that, they provide only a one-time measure of financial inclusion and are not relevant for assessing the changes over time and across nations.Further, a measure of financial inclusion based on the proportion of adults/households with a bank account ignores some other important aspects of an inclusive financial system. These relate to the quality and usage of financial services". " Literature has pointed out that merely having a bank account may not imply that the account is utilized adequately" and introduced the idea of measuring financial inclusion with different dimensions by constructing a comprehensive index.

Sarma (2008) is considered to be the first such study that came up with a complete measure to quantify the level of financial inclusion over the economies by constructing a composite index with three major dimensions of financial inclusion say; banking outreach, availability and usage, by following a methodology similar to the UNDP (United Nations Development Programme) methodology to compute some important development indices such as HDI (Human Development Index) and GDI (Gender Development Index). However, the index constructed in the study is different from UNDP in two major aspects: (a) UNDP follows a simple arithmatic/geomatric mean to combine the dimesional indices to derive the main index whereas, Sarma (2008) adopted a measure of "Normalized Inverse Euclidean Distance" ; and (b) UNDP methodology adopted a pre-fixed measure of maximum and minimum for each dimension to compute the dimensional index whereas, Sarma (2008) replaced this with empirically computed values in her methodology. Hence, the later studies on IFI can be grouped in to (a) study that follows Sarma (2008) methodology and (b) Study that doesn't follow Sarma (2008) methodology are given in the **Table I**.

Table I: Research Methodology Followed in IFI Literature

Methodology	Literature Support	Remarks
Sarma (2008) Methodology	(Chattopadhyay, 2011), (Arora, 2014), (Sethy, 2016), (Goel and Sharma, 2017a), (Gupte et al., 2012),(Yorulmaz, 2018), (Wang and Guan, 2017), (Bozkurt et al., 2018)	• (Gupte et al., 2012), and (Yorulmaz,2018) adopted UNDP's HDI (2010) methodology with Geometric Mean, but (Yorulmaz,2018) assigned weights objectively with Principal Component Analysis (PCA) . • (Wang and Guan, 2017), (Bozkurt et al., 2018) followed same methodology of Sarma (2008), but with objectively assigned weights computed with Co – efficient of Variation (CV) method.
Other than Sarma (2008) or (2012) or (2015)	(Chakravarty and Pal, 2010), (Camera and Tuesta, 2014), (Yadav and Sharma, 2016), (Raichoudhury, 2016), Le et al., (2019)	• (Chakravarty and Pal, 2010) followed axiomatic measurement approach developed in the human development literature. • (Camera and Tuesta, 2014) adopted two – stage PCA. Le et al., (2019) also followed PCA. • (Yadav and Sharma, 2016) used TOPSIS (Technique of order preference by similarity

		to ideal solution), a widely known Multi – Criteria Decision Making (MCDM) technique.

Source: Prepared by Authors

Though, the methodology adopted by Sarma (2008) is widely adopted in the IFI literature, it has faced few criticisms and been disputed with different methodologies for the purpose of measuring financial inclusion in later years. Chakravarty and Pal (2010), stated that the methodology by Sarma (2008) lacks an axiomatic structure, and dimension-wise division of index makes her index to calculate individual percentage contributions impossible. This, in turn, weakens the index in finding the dimensions that are more/less susceptible to global financial inclusion. Cámara et al., (2014), grouped the approaches of index construction into two; (1) parametric and (2) non-parametric methods. Non-parametric methods assign weights exogenously based on researcher's intuition whereas parametric methods use statistically computed weights. They also said that, "there is evidence that indices are sensitive to subjective weight assignment, since a slight change in weights can alter the results dramatically". Hence, the methodology by Sarma (2008) is widely criticized in the literature on this background as the author fixed dimensions weights exogenously.

On par with the adopted methodology, the dimensions and the indicators included in the constructed index play a major role while proposing a new index of financial inclusion. Hence, it has to be studied properly, the same has been analysed and presented in **Table II**. Perhaps, (Gupte et al., 2012) is the study which included maximum number of dimensions/indicators to construct index of financial inclusion followed by Yorulmaz (2018).

Table II: Dimensions Used in IFI Literature

Author	Dimensions
Beck et al. (2007)	(i) Access (ii) Usage
Sarma (2008,2012,2015)	(i) Banking Penetration, (ii) Banking Availability (iii) Usage of Banking Services.
Chattopadhyay (2011)	Same as Sarma (2008)
Chakravarty and Pal (2013)	Same as Sarma (2008)
Camera and Tuesta (2014)	(i) Usage (ii) Barriers (iii) Access
Gupte et al., (2012)	(i) Outreach (Penetration & Accessibility) (ii) Usage (iii) Ease of Transactions (iv) Cost of Transactions
Yorulmaz (2018)	Same as Gupte et al., (2012)
Yadav and Sarma (2016)	Same as Sarma (2008)
Goel and Sharma (2017)	Same as Sarma (2008)

Sethy (2016)	Demand Side Dimensions: (i) Banking Penetration (ii) Availability of Banking Services (iii) Usage of The Banking System Supply Side Dimensions: (iv) Access to Saving (v) Access to Insurance (vi) Bank Risk
Wang and Guan, (2016)	(i) Access (ii) Usage
Bozkurt et al., (2018)	Same as Wang and Guan, (2016)

Source: Prepared by Authors.

Research Methodology:

Data and Sample:

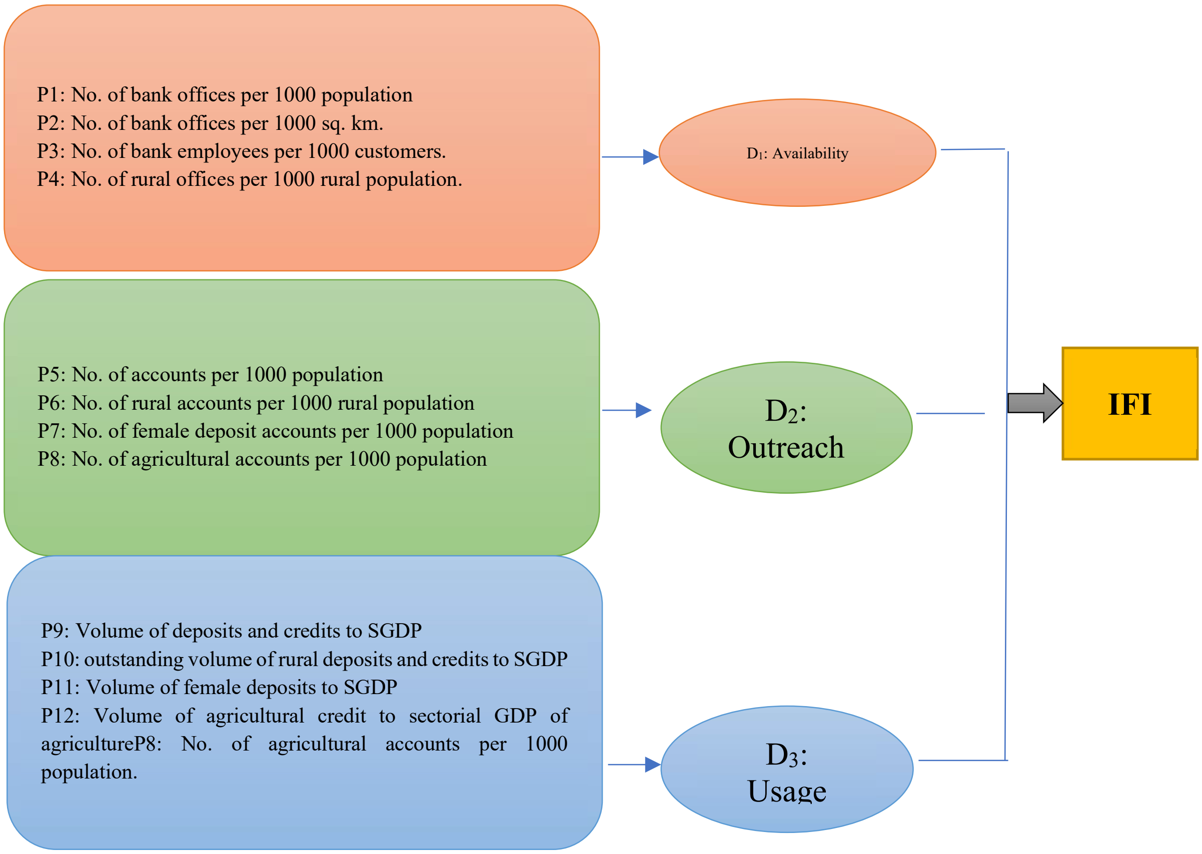
Data for the study includes bank-related, demographical, geographical and economic data. The bank-related data has been collected from “Basic Statistical Returns of Scheduled Commercial Banks” published by Reserve Bank of India (RBI) on an annual basis for the period 2011 and 2017. All the demographical, geographical and economic variables used for this study have been taken from “Handbook of Statistics on Indian States”, an annual publication by RBI. Actual data on demographical variables are available only for the year 2011. Therefore, Data for the same has been projected by using population prediction methods. The sample of the study includes 32 Indian states/UTs.

Index Dimensions and Variables:

In consensus with Sarma (2008), present study constructed an index of financial inclusion with the following dimensions; (1) banking outreach, (2) availability and (3) usage of banking services. The variables included and the proxy used to measure each dimension are presented in

Figure I

Figure I: Dimensions and Performance Measures Used in the Empirical Model



Source: Prepared by Authors

After an extensive literature review, we have found that, Sarma (2008, 2012, 2015), Principal Component Analysis (PCA) and Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) are the major and widely used methodologies in the IFI literature. Hence, this section explains a brief of all these methodologies, which covers the Entropy Weight Method (EWM) used for computing dimensions weight.

Sarma (2008) Methodology:

The IFI by Sarma (2008) captures values between 0 and 1 on a continuum, where, zero indicates the lowest level and 1 describes the highest level of financial inclusion of a country. The computational procedure begins with, the calculation of dimension index by using the formulae;

$$D_i = \frac{X - m}{M - m} \tag{1}$$

If there are **m** dimensions of financial inclusion, then, a country **j** will be represented by a point **Di** = **(d1, d2, d3, …. dm)** on the **m** dimensional cartesian space, where, point **O = (0,0, 0…0)** indicates the worst situation whereas the point **W = (1,1, 1…,1)** describes the fullest attainment in all dimensions. Then the financial inclusion index for the **j**th country, is computed by a "Normalized Inverse Euclidean Distance" of the point **Di** from the ideal point **I = (1,1, 1…,1),** with the formulae;

$$IFI_i = 1 - \frac{\sqrt{(1-d_1)^2 + (1-d_2)^2 + \cdots 1 + (1-d_n)^2}}{\sqrt{n}} \tag{2}$$

Hence, Sarma (2008) constructted a three-dimensional cartesian space with banking penetration(p_i), banking availability(a_i), and banking usage (u_i) such that $0 \leq p_i, a_i, u_i \leq 1$. **Sarma (2012,2015) Methodology:**

Following the base work, author has computed two more IFI in 2012 and 2015. The methodology adopted in these studies are a bit different from the base work, as the study computed final index value as " a simple average of the Euclidian distance between **X** and **O**" (distance from the worst solution) and the " inverse Euclidian distance between **X** and **W**" (distance from the ideal solution) to compute the final index value, where **X** = **(d1 , d2 , d3 , ….,dn)** on the **m**-dimensional space, **O** = **(0, 0, 0,…,0)** shows the point exhibiting the worst situation whereas the point **W = (W_1, W_2, W_3…,W_4)** shows an ideal situation exhibiting the fullest attainment in all dimensions. The formulae used to compute IFI is as follows;

$$\boldsymbol{x_1} = \frac{\sqrt{d_1^2 + d_2^2 + \cdots d_n^2}}{\sqrt{(w_1^2 + w_2^2 + \cdots w_n^2)}} \tag{3}$$

TOPSIS Methodology:

TOPSIS is an important and widely followed Multi Criteria Decision (MCDM) technique, in which alternatives are ranked based on the performance scores computed by using the "Euclidean distance approach". It was basically proposed by Hwang and Yoon (1981). TOPSIS ranks M alternatives based on N criterions if the scores are available for each alternative against different criterions (Bhanot et al., 2015). Hence, there will be M performance scores against M alternatives, based on N criterions, which are computed on the principle that the selected alternative should have the least distance from the positive ideal solution (PIS) and longest distance from the negative ideal solution (NIS) (Tang et al.(2018); Firmialy and Nainggolan(2019); Salmeron et al.(2012); Krohling and Pacheco(2015); Freeman and Chen(2015); Guler Aras, Nuray Tezcan, and Ozlem Kutlu Furtuana(2016); and Bhanot and Bapat(2015)).

The computational procedure of TOPSIS starts with the building of a normalized **M×N** decision matrix with the formulae;

$$\boldsymbol{r_{ij}} = \frac{\boldsymbol{x_{ij}}}{\sqrt{\sum_{i=1}^{M}(x_{ij})^2}} \tag{6}$$

where, $\mathbf{x_{ij}}$ **(i€M; j€N)** represents each element of the **M×N** matrix.
Then, a relative weight will be assigned to each criterion in the constructed matrix either objectively or subjectively, to construct a weighted normalisation matrix with the formulae;

$$\boldsymbol{v_{ij} = w_j r_{ij}} \tag{7}$$

where, $\mathbf{w_j}$ represents weight assigned to each criterion and $\mathbf{r_{ij}}$ represents the normalised $\mathbf{x_{ij}}$ values. The present study constructed assigned the weights objectively with EWM to make the comparison of the methodologies meaningful.

TOPSIS ranks alternatives based on the positive ideal and negative ideal solution, hence, each criterion either to be maximised or minimised to get the best alternative known as positive ideal (**A***) and worst alternative known as negative ideal (**A-**). The rule of thumb is that, the beneficial criterion is to be maximised and the non-beneficial criterion to be minimised. **A*** and **A-** defined as;

$$A^* = \begin{cases} \binom{\max}{j} v_{ij} \;\; \forall\, i \; when\; criteria\; j\; is\; to\; be\; maximized \\ \binom{min}{j} v_{ij} \;\; \forall\, i \; when\; criteria\; j\; is\; to\; be\; minimized \end{cases} = \; v_1^*, v_2^*, v_3^* \tag{8}$$

$$A^- = \begin{cases} \binom{\min}{j} v_{ij} \;\; \forall\, i \; when\; criteria\; j\; is\; to\; be\; maximized \\ \binom{max}{j} v_{ij} \;\; \forall\, i \; when\; criteria\; j\; is\; to\; be\; minimized \end{cases} = \; v_{1-}, v_{2-}, v_{-3} \tag{9}$$

Next step is to compute the distance measure for each alternative from the positive ideal, $\mathbf{S_i}^*$, and negative ideal, $\mathbf{S_i}^*$, with the formulae:

$$\boldsymbol{s_i^*} = \sqrt{\textstyle\sum_{j=1}^{3}\left(\boldsymbol{v_{ij-}}\; \boldsymbol{v_j^*}\right)}, \text{for i} = 1,2,3, \ldots.,32. \tag{\textbf{10}}$$

$$\boldsymbol{s_i^-} = \sqrt{\textstyle\sum_{j=1}^{3}\left(\boldsymbol{v_{ij-}}\; \boldsymbol{v_j^-}\right)}, \text{for i} = 1,2,3, \ldots.,32. \tag{11}$$

Then a relative closeness measure to the ideal solution from each alternative is computed (the value ranges between 0 and 1, higher value indicates better performance) with the formulae;

$$\boldsymbol{c_i^*} = \frac{\boldsymbol{S_{i-}}}{\mathbf{S}_{\boldsymbol{i*}} + \boldsymbol{S_{i-}}} \tag{\textbf{12}}$$

Finally ranks are assigned to each alternative in descending order based on their relative closeness to the ideal solution.

PCA Methodology:

The Principal Component Analysis (PCA), is an important multivariate technique used for data reduction, originally proposed by the British biostatistician Karl Pearson in 1901. The underlying principle of PCA is to minimize the dimensionality of data by keeping the maximum possible variations in the dataset. Hence, PCA coverts a number of possibly correlated variables into a smaller number of uncorrelated variables, known as Principal Components (PCs) or latent variables, "which are linear combinations of optimally weighted original variables calculated with the maximum variance criterion which are uncorrelated, and ordered from largest to smallest variance" Jolliffe (2003), and Cios, (2007). The maximum number of components extracted always equals the number of variables.

Weights assigned to the dimensions are calculated objectively by following a "two-stage Principal Component Analysis" in confirmation with (Camera and Tuesta, 2014) to compare the results with other methodologies in the IFI literature. Hence, First, we employ PCA to compute a group of three sub-indices of financial inclusion: availability, outreach and usage. In the second stage, we calculate the dimension weights and the overall financial inclusion index by employing the previous sub-indices as causal or explanatory variables. Hence, we have to begin with the three unobserved endogenous variables $\mathbf{Y_i^a}$, $\mathbf{Y_i^o}$, $\mathbf{Y_i^u}$ and the parameters in the following system of equations to estimate the dimensions:

$$Y_i^a = \beta_1\, P_{1i} + \beta_2\, P_{2i} + \beta_3\, \mathrm{P}_{3i} + \beta_4\, \mathrm{P}_{4i} + \mathrm{u_i} \tag{13}$$

$$Y_i^b = \theta_1\, P_{5i} + \theta_2\, P_{6i} + \theta_3\, P_{7i} + \theta_4\, P_{8i} + €_i \tag{14}$$

$$\mathrm{Y_i^u} = \alpha_1\, \mathrm{P}_{9i} + \alpha_2\, \mathrm{P}_{10i} + \alpha_3\, \mathrm{P}_{11i} + \alpha_4\, \mathrm{P}_{12i} + \mathrm{v_i} \tag{15}$$

where, **β, θ,** and **α** are unknown parameters used to estimate the unobserved endogenous variables. **P1, P2………………………., P12** are the variables included in the present study as explained in the Figure I. Hence, we get three principal components as linear functions of the latent variables. The principal component so arrived with corresponding weights are described in **Table III**.

EWM:

In consensus with Li et al., (2014); Aras et al., (2016); and Liu and Zhang, (2011), the present study computed weights objectively with entropy method to make the comparison of selected methodologies meaningful and weights are presented in **Table III**. The computational procedure is as follows;

With **m** indicators and **n** samples in the data set for the evaluation of weights, the value measured can be denoted as x_{ij}. The decision matrix, $\{r_{ij}\}$ can be developed by performing the standardisation of the values measured (Aras et al., 2017; Ding et al., 2016; Dong et al., 2010). The formula for the standardisation is as follows:

$$r_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{16}$$

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

$$e_i = \frac{\sum_{j=1}^{n} r_{ij} \ln r_{ij}}{-\ln n} \tag{17}$$

The entropy value ranges between **0** and **1**. The entropy value can also be called as 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

$$w_i = \frac{1 - e_i}{\sum_{i=1}^{m}(1 - e_i)} \tag{18}$$

Discussion of Results:

Table **IV & Table V** depict the descriptive statistics of the IFI values of Indian states/UTs based on the four methodologies in consideration with the present study. In which, **Table IV** shows the descriptive statistics of IFI values with the objective weights (TOPSIS, Sarma (2008,2015) are constructed with the weights calculated with EWM, and Camera and Tuesta, (2014) with two stage PCA as explained in the methodology section). Whereas, **Table V** depicts the descriptive statistics of the index values computed with the subjective weights as in the studies of Sarma (2008, 2015). "There is evidence that indices are sensitive to the subjective weight assignment, since a slight change in weights can alter the results dramatically" Camera and Tuesta, (2014). Out of the methodology in consideration with the present study, Sarma (2008,2012 and 2015) are prone to this criticism as they computed IFI with subjective weights. To verify this claim, we computed Sarma (2008, 2012 and 2015) indices with both subjective (exactly as in the original paper) and objective weights (in which weights are computed with EWM) and the results are presented in **Table VI and Table VIII**. Though Sarma (2008, 2012, and 2015) are considered for the comparison initially, only Sarma (2008) and Sarma (2012) are included in the analysis and discussion part, as we have found that Sarma (2012, 2015) follows the similar formulae and methodology to compute the IFI index.

There is a 7 per cent increase in the general financial inclusion performance in India in terms of average performance as per the both methodologies of TOPSIS with EWM and Sarma (2015) with EWM. Whereas, Sarma (2008) with EWM methodology shows only 5 per cent improvement in financial inclusion. On the other hand, Camera and Tuesta, (2014) with two – stage PCA recorded 20% hike in financial inclusion performance in India in general (see **Table IV**). At the same time, **Table V** exhibits a 26 per cent and 23 per cent improvements in financial inclusion performance in India based on Sarma (2008, 2015) with subjective weights. These figures, clearly tells that, claim by Camera and Tuesta, (2014) is valid and an index with subjective weight shows an inflated financial inclusion performance.

Further, the effects of the weights assigned to the indicators during the index construction are very clear from the individual state performance fluctuation in terms of IFI values and the ranks assigned based on the different methodologies in comparison (See **Table**; **VI, VII, VIII, and IX**). **Table VII** and **Table IX** can give more insight on this aspect which compares Sarma (2008,2015) methodology performance (both in terms of IFI values and the ranks) with the subjective and objective weights assigned. Two major points to be noted here are that, (1) An IFI constructed with the methodologies (TOPSIS with EWM and Sarma (2015) with EWM) shows an almost similar performance in terms of Mean, Range and the Standard Deviation values in both years (see **Table IV**), (2) There is only a slight difference in the financial inclusion performance based on Camera and Tuesta, (2014) with two – stage PCA and Sarma (2008, 2015) with the subjective weights based on the descriptive statistics say, Mean, Range and Standard Deviation (compare **Table IV** and **Table V**). Hence, the reasons for the same needs to be identified.

A detailed analysis on this background has been carried out, and found that, the dimension weights assigned by two-stage PCA methodology are very narrow (means, weights are almost equal for each dimensions) in comparison with the dimension weights based on EWM, See **Table III**. In PCA, the weights of the indicators are calculated based on their loadings with the components. The loadings of the components, at first place are calculated based on the correlations of the indicators with other indicators. When the correlations of indicators with a component are equal, the weights of those variables will also be equal. Thus, it is clear that the PCA based weights considers the relative positions of the indicators in an '**n**' dimensional space.

On the other hand, in EWM, the weights of the indicators are determined by the entropy. Information entropy describes the degree of uncertainty in the system (Shannon, 1948) and thus it is the measure of the degree of disorder in a system. If the entropy is smaller, the weight of the indicator will be greater (Zheng and Tang, 2020). When the values of elements in an indicator are the same, the indicator doesn't have any valuable information. Thus, the entropy will be **1** and the weight of the indicator will be **0**. If the differences among the values in an indicator is greater, the entropy will be smaller and the weight of the indicator will be high, as it is being considered to possess more information (Chen, 2020). This makes clear that unlike PCA, entropy method is based on the inherent information of the indicator.

Moreover, a comparison of the methodology of TOPSIS proposed by Yadav & Sarma (2016), and a "distance–based" approach by Sarma (2015) shows that there is a higher similarity among these two methodologies; (1) both the methodologies follow "Euclidean – distance approach", and (2) the IFI value is computed as an " average distance from an ideal and a worst solution with a common underlying principle of high value of IFI will indicate a low distance from the ideal outcome and high distance from the worst outcome". Hence, these two methodologies [TOPSIS and Sarma (2015)] shows the same average performance. This can be further confirmed with the individual IFI scores of Indian states/UTs presented in **Table VI** and the rank assigned in **Table VIII**. We can find, an almost similar IFI scores and rank in both years based on these methodologies.

A comparison of Indian states/UTs performance on financial inclusion shows that, UT of Chandigarh retains the first position in both the years, irrespective of the methodology adopted and the weight assigned (see **Table VIII** and **Table IX**). In the same way, UT of Delhi retains the second position, except in 2017 based on PCA methodology. Third and Fourth positions are retained by Goa and UT of Puducherry. In general, Union Territories perform better on financial inclusion in India, one reason could be attributed to this is that, 'population density' as union territories cover lesser geographical area with higher number of populations. Manipur and Nagaland are the two least scored states in in both years based on all the index compared in this study (**Table; VI, VII, VIII, IX**).

As discussed above, dimension weights assigned by a two - stage PCA also denoted as Camera and Tuesta (2014) methodology is very narrow. To overcome this barrier, we are proposing a modified method, in which the weights of the variables in the first stage are calculated by

$$w_j = \frac{\sum_{k=1}^{k} r_{jk}\lambda_k}{\sum_{k=1}^{k} r_{jk}} \tag{19}$$

$$\beta_j = \frac{w_j}{\sum_{j=1}^{j} w_j} \tag{20}$$

The change here is that each loading of a variable is divided by the sum of all the loadings of that variable, $\sum \boldsymbol{r_j}$ in order to make the distance among the components with respect to the loadings meaningful across all the variables. Similarly, in the second stage, the weights are calculated as

$$w_d = \frac{\sum_{d=1}^{d} R_{dk}\lambda_k}{\sum_{d=1}^{d} R_{dk}} \tag{21}$$

$$W_d = \frac{w_d}{\sum_{d=1}^{d} w_d} \tag{22}$$

The result of the proposed methodology is given in **Table X, XI and XII**. From the **Table X** we can see that, the new methodology proposed in this study gives wider weights in comparison with Camera and Tuesta (2014) dimension weights. Financial inclusion performance with the proposed PCA in this study shows more closer performance in comparison with TOPSIS and Sarma (2015) methodology (in terms of descriptive statistics) with dimensions weight assigned with EWM. It can be observed from **Table XII**, and performance of the states in terms of IFI values and rank can be observed from **Table XI**.

Conclusion, Limitation and Future Scope of Study:

The study has been carried out on the background that, there exists conflict over the methodologies (Camara & Tuesta, 2014; Chakravarty & Pal, 2010; Gupte et al., 2012; Sarma, 2008, 2012, 2015; Yadav & Sharma, 2016) adopted to construct financial inclusion index in the literature in terms of performance accuracy, and efficiency. This study aimed at comparing the financial inclusion performance variation of four important methodologies in the IFI literature say; Sarma (2008), Sarma (2015), two-stage PCA by Camera and Tuesta (2014), and TOPSIS.

Through this study, we have observed that: (1) An IFI constructed with the methodologies (TOPSIS with EWM and Sarma (2015) with EWM) shows an almost similar performance in terms of descriptive statistics in both years; and (2) There is only a slight difference in the financial inclusion performance based on Camera and Tuesta, (2014) with two-stage PCA and Sarma (2008, 2015) with the subjective weights based on the descriptive statistics. We also find that, the dimension weights assigned by two-stage PCA methodology are very narrow (means, weights are almost equal for each dimension) in comparison with the dimension weights based on EWM, hence it shows an almost similar performance with the performance of studies by Sarma (2008, 2015) with the subjective weights. Further, TOPSIS and Sarma (2015) follows; (1) “Euclidean distance approach”, and (2) the IFI value is computed as an average distance from an ideal and a worst solution. Hence, these methodologies provide almost similar financial inclusion performance. Other findings from the study are that: (1) IFI are subject to the dimensional weight assigned; (2) UT of Chandigarh retains the first position, UT of Delhi retains the second position, third and fourth positions are retained by Goa and UT of Puducherry; (3) In general, Union Territories perform better on financial inclusion in India, one reason could be attributed to this is that, ‘population density’; and (4) Manipur and Nagaland are the two least scored states in both years.

We have proposed an improved two-stage PCA model against the model of Camara and Tuesta (2014), and the result shows that: (1) the new methodology proposed gives wider weights; and (2) the financial inclusion performance with the proposed two-stage PCA shows more closer performance in comparison with TOPSIS and Sarma (2015) methodologies with objective weights. Hence, we conclude that, the two–stage PCA by Camera and Tuesta (2014) captures only narrow dimension weights from the data, hence it may not capture true financial inclusion performance. Moreover, PCA is not useful for IFI construction as it captures the second moments from the variance – covariance of the dimensions, instead of first moments and it will ensure only the issue of multidimensionality and will not meet the other desirable properties proposed by Sarma (2015). On the other hand, a methodology by Sarma (2015), and TOPSIS meets all these properties along with multi-dimensionality, and computational easiness. As IFI are sensitive to the dimensional weight assigned, these methodologies should be integrated with a statistical method which captures the true weight of the dimensions from the data. Entropy Weight Method is one such a good option, hence future studies can be carried out with an EWM integrated Sarma (2015) or TOPSIS methodology.

The present study is useful to all the stakeholders who are interested in the measurement of financial inclusion. It can be useful to the policymakers to account the progress of policy initiatives undertaken, to the academic and research communities who are interested in measurement of financial inclusion and to test different hypothesis in the financial inclusion literature. The present study faces few limitations; (1) It has eliminated some other important methodologies, say “axiomatic approach” by Chakravarty & Pal, (2010), (2) PCA has been used in IFI literature in different fashion by Le et al., (2019) and (Yorulmaz, 2018), the present study has ignored these studies to keep the paper short and simple, (3) the study has been carried out only for the year 2011 and 2017, with a small sample data, and (4) the major focus of the study is on performance comparison rather than on technical aspects. Hence, future study can be carried out by overcoming the limitations of the present study.

Table III: A Comparison of Dimensional Weights Based on EWM and PCA

Performance Measures	EWM		PCA	
	2011	2017	2011	2017
Dimension 1: Availability			**0.301**	**0.310**
P1	0.004	0.009	0.244	0.259
P2	0.023	0.024	0.256	0.241
P3	0.263	0.305	0.234	0.266
P4	0.085	0.054	0.266	0.234
Dimension 2: Outreach			**0.308**	**0.312**
P5	0.023	0.014	0.262	0.275
P6	0.092	0.038	0.239	0.230
P7	0.035	0.019	0.251	0.271
P8	0.065	0.074	0.249	0.225
Dimension 3: Usage			**0.301**	**0.291**
P9	0.032	0.026	0.311	0.328
P10	0.019	0.033	0.102	0.016
P11	0.018	0.016	0.327	0.340
P12	0.340	0.388	0.259	0.315

Source: Computed by Authors.

Table IV: A Comparison of Descriptive Statistics of IFI Values with Objective Weights

Source: Computed by Authors.

Methodology	Year	Range	Min.	Max.	Mean	SD
TOPSIS with EWM	2011	0.978	0.003	0.981	0.067	0.176
	2017	0.931	0.006	0.937	0.074	0.181
Sarma (2008) with EWM	2011	0.961	0.003	0.964	0.055	0.031
	2017	0.896	0.003	0.899	0.060	0.031
Sarma (2015) with EWM	2011	0.976	0.004	0.980	0.070	0.176
	2017	0.935	0.007	0.942	0.077	0.181
PCA with (Camera and Tuesta, 2014)	2011	0.834	0.012	0.847	0.162	0.028
	2017	0.792	0.030	0.822	0.182	0.028

Table V: A Comparison of Descriptive Statistics of IFI Values with Subjective Weights

Methodology	Year	Range	Min.	Max.	Mean	SD
Sarma (2008)	2011	0.774	0.018	0.793	0.160	0.025
	2017	0.620	0.046	0.666	0.186	0.022
Sarma (2015)	2011	0.827	0.030	0.857	0.196	0.028
	2017	0.706	0.061	0.767	0.219	0.026

Source: Computed by Authors.

Table VI: A Comparison of IFI Values with Objective Weights

	TOPSIS with EWM		**Sarma2008 with EWM**		**Sarma2015 with EWM**		**PCA with (Camera and Tuesta, 2014)**	
	2011	**2017**	**2011**	**2017**	**2011**	**2017**	**2011**	**2017**
Chandigarh	0.981	0.937	0.964	0.899	0.980	0.942	0.847	0.822
Delhi	0.317	0.517	0.276	0.507	0.329	0.518	0.463	0.508
Goa	0.103	0.091	0.052	0.035	0.102	0.096	0.448	0.520
Puducherry	0.096	0.129	0.073	0.088	0.109	0.131	0.233	0.275
Tamil Nadu	0.059	0.065	0.030	0.032	0.066	0.063	0.196	0.210
Kerala	0.050	0.055	0.032	0.034	0.058	0.055	0.221	0.207
Andhra Pradesh	0.044	0.037	0.022	0.019	0.048	0.038	0.150	0.159
Himachal Pradesh	0.041	0.046	0.021	0.016	0.043	0.051	0.179	0.211
Karnataka	0.034	0.030	0.023	0.020	0.041	0.033	0.199	0.189
Punjab	0.033	0.041	0.025	0.027	0.041	0.048	0.201	0.247
Uttarakhand	0.027	0.027	0.018	0.016	0.030	0.032	0.140	0.173
Sikkim	0.026	0.025	0.011	0.009	0.024	0.026	0.121	0.151
Maharashtra	0.025	0.022	0.015	0.013	0.031	0.025	0.180	0.183
Haryana	0.024	0.027	0.019	0.021	0.029	0.031	0.131	0.178
Andaman & Nicobar Islands	0.022	0.021	0.009	0.008	0.021	0.023	0.101	0.144
Jammu & Kashmir	0.022	0.026	0.010	0.010	0.026	0.030	0.144	0.181
Mizoram	0.021	0.021	0.011	0.008	0.020	0.021	0.096	0.101
Odisha	0.019	0.020	0.013	0.009	0.022	0.023	0.090	0.105
Uttar Pradesh	0.019	0.022	0.015	0.015	0.023	0.026	0.089	0.103

Gujarat	0.018	0.017	0.013	0.012	0.022	0.020	0.114	0.130
West Bengal	0.018	0.024	0.015	0.016	0.021	0.028	0.101	0.146
Tripura	0.018	0.031	0.011	0.015	0.020	0.033	0.078	0.144
Arunachal Pradesh	0.015	0.016	0.006	0.004	0.017	0.018	0.081	0.076
Bihar	0.014	0.020	0.012	0.014	0.018	0.024	0.059	0.067
Rajasthan	0.014	0.016	0.010	0.011	0.017	0.018	0.079	0.089
Meghalaya	0.014	0.022	0.008	0.008	0.018	0.025	0.125	0.119
Jharkhand	0.013	0.019	0.010	0.010	0.016	0.022	0.071	0.099
Madhya Pradesh	0.012	0.013	0.010	0.008	0.015	0.015	0.079	0.075
Assam	0.011	0.017	0.008	0.010	0.013	0.019	0.057	0.083
Chhattisgarh	0.010	0.012	0.009	0.007	0.012	0.015	0.052	0.069
Nagaland	0.005	0.006	0.003	0.003	0.007	0.007	0.056	0.046
Manipur	0.003	0.009	0.003	0.004	0.004	0.011	0.012	0.030

Source: Computed by Authors.

Table VII: A Comparison of IFI Values with Objectives and Subjective Weights

	Sarma2008		**Sarma2015**		**Sarma2008 with EWM**		**Sarma2015 with EWM**	
	2011	**2017**	**2011**	**2017**	**2011**	**2017**	**2011**	**2017**
Chandigarh	0.793	0.666	0.857	0.767	0.964	0.899	0.980	0.942
Delhi	0.378	0.444	0.469	0.503	0.276	0.507	0.329	0.518
Goa	0.362	0.422	0.486	0.562	0.052	0.035	0.102	0.096
Puducherry	0.217	0.256	0.274	0.323	0.073	0.088	0.109	0.131
Tamil Nadu	0.189	0.214	0.232	0.247	0.030	0.032	0.066	0.063
Kerala	0.198	0.190	0.250	0.232	0.032	0.034	0.058	0.055
Andhra Pradesh	0.153	0.172	0.182	0.192	0.022	0.019	0.048	0.038
Himachal Pradesh	0.193	0.251	0.272	0.321	0.021	0.016	0.043	0.051
Karnataka	0.193	0.198	0.226	0.214	0.023	0.020	0.041	0.033
Punjab	0.209	0.276	0.245	0.312	0.025	0.027	0.041	0.048
Uttarakhand	0.156	0.197	0.181	0.219	0.018	0.016	0.030	0.032
Sikkim	0.135	0.164	0.171	0.196	0.011	0.009	0.024	0.026
Maharashtra	0.161	0.171	0.203	0.205	0.015	0.013	0.031	0.025
Haryana	0.137	0.186	0.154	0.206	0.019	0.021	0.029	0.031
Andaman & Nicobar Islands	0.113	0.167	0.137	0.187	0.009	0.008	0.021	0.023
Jammu & Kashmir	0.152	0.207	0.204	0.246	0.010	0.010	0.026	0.030
Mizoram	0.101	0.110	0.126	0.129	0.011	0.008	0.020	0.021
Odisha	0.107	0.131	0.129	0.151	0.013	0.009	0.022	0.023
Uttar Pradesh	0.100	0.125	0.128	0.149	0.015	0.015	0.023	0.026
Gujarat	0.118	0.139	0.135	0.151	0.013	0.012	0.022	0.020
West Bengal	0.109	0.159	0.126	0.181	0.015	0.016	0.021	0.028
Tripura	0.093	0.168	0.114	0.190	0.011	0.015	0.020	0.033
Arunachal Pradesh	0.098	0.102	0.135	0.126	0.006	0.004	0.017	0.018
Bihar	0.074	0.091	0.109	0.121	0.012	0.014	0.018	0.024
Rajasthan	0.087	0.106	0.099	0.115	0.010	0.011	0.017	0.018
Meghalaya	0.130	0.145	0.174	0.181	0.008	0.008	0.018	0.025

Jharkhand	0.085	0.119	0.103	0.139	0.010	0.010	0.016	0.022
Madhya Pradesh	0.086	0.087	0.101	0.097	0.010	0.008	0.015	0.015
Assam	0.069	0.103	0.084	0.119	0.008	0.010	0.013	0.019
Chhattisgarh	0.061	0.083	0.070	0.097	0.009	0.007	0.012	0.015
Nagaland	0.057	0.052	0.080	0.077	0.003	0.003	0.007	0.007
Manipur	0.018	0.046	0.030	0.061	0.003	0.004	0.004	0.011

Source: Computed by Authors.

Table VIII: States/UTs Rank with Objective Weights

	TOPSIS with EWM		**Sarma2008 with EWM**		**Sarma2015with EWM**		**PCA with (Camera and Tuesta, 2014)**	
	2011	**2017**	**2011**	**2017**	**2011**	**2017**	**2011**	**2017**
Chandigarh	1	1	1	1	1	1	1	1
Delhi	2	2	2	2	2	2	2	3
Goa	3	4	4	4	4	4	3	2
Puducherry	4	3	3	3	3	3	4	4
Tamil Nadu	5	5	6	6	5	5	8	7
Kerala	6	6	5	5	6	6	5	8
Andhra Pradesh	7	9	9	10	7	9	11	14
Himachal Pradesh	8	7	10	12	8	7	10	6
Karnataka	9	11	8	9	9	10	7	9
Punjab	10	8	7	7	10	8	6	5
Uttarakhand	11	12	12	11	12	12	13	13
Sikkim	12	15	20	24	15	17	16	15
Maharashtra	13	18	15	17	11	18	9	10
Haryana	14	13	11	8	13	13	14	12
Andaman & Nicobar Islands	15	21	26	27	19	21	19	17
Jammu & Kashmir	16	14	24	21	14	14	12	11
Mizoram	17	20	21	26	21	24	20	23
Odisha	18	23	16	23	18	22	21	21
Uttar Pradesh	19	17	14	14	16	16	22	22
Gujarat	20	26	17	18	17	25	17	19
West Bengal	21	16	13	13	20	15	18	16
Tripura	22	10	19	15	22	11	26	18
Arunachal Pradesh	23	27	30	30	7	9	23	27
Bihar	24	22	18	16	23	20	28	30
Rajasthan	25	28	22	19	25	27	25	25
Meghalaya	26	19	28	25	24	19	15	20
Jharkhand	27	24	23	20	27	23	27	24
Madhya Pradesh	28	29	25	28	28	29	24	28
Assam	29	25	29	22	29	26	29	26
Chhattisgarh	30	30	27	29	30	30	31	29
Nagaland	31	32	31	32	31	32	30	31

Manipur	32	31	32	31	32	31	32	32

Source: Computed by Authors.

Table IX: A Comparison of States/UTs Rank with Subjective and Objective Weights

	Sarma2008		**Sarma2015**		**Sarma2008 with EWM**		**Sarma2015 with EWM**	
	2011	**2017**	**2011**	**2017**	**2011**	**2017**	**2011**	**2017**
Chandigarh	1	1	1	1	1	1	1	1
Delhi	2	2	3	3	2	2	2	2
Goa	3	3	2	2	4	4	4	4
Puducherry	4	5	4	4	3	3	3	3
Tamil Nadu	9	7	8	7	6	6	5	5
Kerala	6	11	6	9	5	5	6	6
Andhra Pradesh	12	13	12	15	9	10	7	9
Himachal Pradesh	7	6	5	5	10	12	8	7
Karnataka	8	9	9	11	8	9	9	10
Punjab	5	4	7	6	7	7	10	8
Uttarakhand	11	10	13	10	12	11	12	12
Sikkim	15	17	15	14	20	24	15	17
Maharashtra	10	14	11	13	15	17	11	18
Haryana	14	12	16	12	11	8	13	13
Andaman & Nicobar Islands	18	16	17	17	26	27	19	21
Jammu & Kashmir	13	8	10	8	24	21	14	14
Mizoram	21	24	23	24	21	26	21	24
Odisha	20	21	20	21	16	23	18	22
Uttar Pradesh	22	22	21	22	14	14	16	16
Gujarat	17	20	19	20	17	18	17	25
West Bengal	19	18	22	19	13	13	20	15
Tripura	24	15	24	16	19	15	22	11
Arunachal Pradesh	23	27	18	25	30	30	7	9
Bihar	28	28	25	26	18	16	23	20
Rajasthan	25	25	28	28	22	19	25	27
Meghalaya	16	19	14	18	28	25	24	19
Jharkhand	27	23	26	23	23	20	27	23
Madhya Pradesh	26	29	27	29	25	28	28	29
Assam	29	26	29	27	29	22	29	26
Chhattisgarh	30	30	31	30	27	29	30	30
Nagaland	31	31	30	31	31	32	31	32
Manipur	32	32	32	32	32	31	32	31

Source: Computed by Authors.

Table X: A Comparison of Dimension Weights with Two – Stage PCA and Proposed Methodology

Performance Measures	PCA (Camera and Tuesta,2014)		PCA (Present study)	
	2011	2017	2011	2017
Dimension 1: Availability	**0.301**	**0.310**	**0.436**	**0.412**
P1	0.244	0.259	0.182	0.222
P2	0.256	0.241	0.127	0.438
P3	0.234	0.266	0.409	0.119
P4	0.266	0.234	0.282	0.221
Dimension 2: Outreach	**0.308**	**0.312**	**0.242**	**0.206**
P5	0.262	0.275	0.278	0.339
P6	0.239	0.230	0.387	0.247
P7	0.251	0.271	0.212	0.284
P8	0.249	0.225	0.123	0.130
Dimension 3: Usage	**0.301**	**0.291**	**0.321**	**0.381**
P9	0.311	0.328	0.189	0.296
P10	0.102	0.016	0.076	0.021
P11	0.327	0.340	0.202	0.389
P12	0.259	0.315	0.533	0.293

Source: Computed by Authors.

Table XI: IFI Values Based on Proposed PCA Calculation

	2011		2017	
	IFI	Rank	IFI	Rank
Chandigarh	0.955	1	0.915	1
Delhi	0.447	2	0.543	3
Goa	0.372	3	0.617	2
Puducherry	0.177	4	0.256	6
Tamil Nadu	0.136	10	0.205	12
Kerala	0.158	5	0.228	7
Andhra Pradesh	0.104	14	0.162	16
Himachal Pradesh	0.147	7	0.259	5
Karnataka	0.147	8	0.210	10
Punjab	0.157	6	0.303	4
Uttarakhand	0.115	11	0.208	11
Sikkim	0.109	13	0.186	14
Maharashtra	0.137	9	0.204	13
Haryana	0.102	16	0.212	9
Andaman & Nicobar Islands	0.088	18	0.177	15
Jammu & Kashmir	0.113	12	0.216	8
Mizoram	0.085	19	0.129	21
Odisha	0.075	21	0.122	22
Uttar Pradesh	0.066	23	0.119	23

Gujarat	0.090	17	0.150	19
West Bengal	0.084	20	0.160	17
Tripura	0.061	25	0.145	20
Arunachal Pradesh	0.067	22	0.095	26
Bihar	0.046	29	0.075	30
Rajasthan	0.061	26	0.100	25
Meghalaya	0.103	15	0.154	18
Jharkhand	0.058	27	0.112	24
Madhya Pradesh	0.062	24	0.083	28
Assam	0.046	30	0.083	27
Chhattisgarh	0.041	31	0.078	29
Nagaland	0.048	28	0.057	31
Manipur	0.011	32	0.027	32

Source: Computed by Authors.

Table XII: A Comparison of Descriptive Statistics of Proposed PCA Methodology with TOPSIS and Sarma (2015)

Methodology	Year	Range	Min.	Max.	Mean	SD
Proposed Methodology	2011	0.944	0.011	0.955	0.140	0.173
	2017	0.888	0.027	0.915	0.206	0.178
TOPSIS with EWM	2011	0.978	0.003	0.981	0.067	0.176
	2017	0.931	0.006	0.937	0.074	0.181
Sarma (2015) with EWM	2011	0.976	0.004	0.980	0.070	0.176
	2017	0.935	0.007	0.942	0.077	0.181

Source: Computed by Authors.

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