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CONSTRUCTING A COMPOSITE INDEX OF FDI ATTRACTIVENESS: A CASE STUDY

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Abstract: The paper proposes a methodology of deriving a composite index of regional FDI attractiveness scores. By adopting a research methodology that is deductive in nature, the paper first selects a set of variables (proxies) which seeks to include all the identifiable, measurable, and comparable aspects affecting the inflow of FDI. The paper next aggregates these variables using the technique of TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) used in Multiple Criteria Decision Making (MCDM). Regional rankings based on actual per-capita FDI inflows are next compared with those based on TOPSIS based composite rankings. Regional difference in actual FDI inflows can thus be attributed to differences in regional FDI attractiveness scores.

Keywords: FDI Inflow, Composite Score, FDI Attractiveness Score, TOPSIS, Entropy

1. Introduction.

The literature available on FDI is vast. The decision making process of a foreign investor being complex in nature, no consensus has yet been reached about a set of robust location determinants of FDI. The question arises: why does FDI flow to some select countries only, while the other similarly capital-scarce countries do not receive such inflows in adequate amounts? Are the specific policies and socio-economic conditions (e.g. the level and quality of infrastructure, skill of workers, etc.) of a country relevant for attracting sufficient FDI inflows in important areas? This question is no less relevant, and perhaps more important, in the context of FDI inflows even in a given country when there are marked variations in such inflows across its different regions. The issue is not a hypothetical one, as we do observe such significant *interregional variations* in amounts of FDI inflows in the context of the Indian economy. It is observed that the economically advanced states like Maharashtra, Delhi, Karnataka, Tamil Nadu, Gujarat, and Andhra Pradesh have been benefitted by the bulk of the inflows while states like Bihar, Uttar Pradesh, and Odisha have only got a trickle. The underlying reason must be that there are some region-specific features which reflect the relative attractiveness of these regions as far as inflows of FDI are concerned. The purpose of the present exercise is precisely to analyse this issue, i.e., to construct an index of attractiveness of each region in terms of potential FDI inflows. In particular, we would like to assess empirically the various socio-economic factors that are likely to account for such marked interregional variations in FDI inflows in India. The paper next proposes a methodology so as to aggregate the various determinants of FDI inflows into a single composite index of FDI attractiveness. The proposed FDI attractiveness index in essence considers all identifiable major measurable and comparable aspects that affect FDI decisions. As a result regions can be ranked in terms of their FDI attractiveness scores. Regions with a higher FDI scores are supposed to draw higher inflows of FDI in comparison to ones having lower values of the same.

With the aforesaid purpose in view, the paper is organized as follows. Section 2 elaborates the methodology together with a comprehensive analysis of the existing empirics. Section 3 describes a case study of measuring composite FDI attractiveness scores using the proposed methodology. Section 4 concludes by drawing up the policy implications of the findings.

2. Methodology

This study is based on deductive reasoning; deductive in the sense that the research begins with a theory that has been built upon a specific hypothesis subsequently to be tested by collecting data. Empirical generalizations made on the basis of the data are to be linked to the theory[1]. We explicitly derive a concept of multiple studies which are synthesized to allow for a systematic comparison and cross-study conclusion[2]**.** The research questions formulated in the problem statement provide a sound starting point for the meta-study.

The study starts with the construction of a composite (FDI attractiveness) index for each region *i* (C_i') for each year. The concept is based on the notion of "Multiple Criteria Decision Making" (MCDM) analysis, a sub-discipline of Operations Research that explicitly considers multiple criteria in decision-making environments. The specific MCDM methodology adopted in this paper is TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) developed by Hwang & Yoon (1981). We describe this technique below.

Assuming that there are *n* regions and *m* number of potential determinants (criteria) of FDI, the basic premise behind TOPSIS is the data matrix X= $\left[(x_{ij})\right]_{n\times m}$ where x_{ij} denotes the value of the j^{th} attribute for the i^{th} region. Assuming that the utilities derived from some of the criteria in X are monotonically increasing (which are thus termed as the *benefit attributes*) and the same for the remaining attributes are monotonically decreasing (which are thus termed as the *cost attributes*), $C_i{}'$s are estimated by integrating the elements of the i^{th} row of X with reference to some ideal and negative ideal situations (Lertprapai 2013). In the absence of any natural ideal and non-ideal solutions, though, optimal solution to the MCDM problem is obtained by defining two *artificial points* in the m-dimensional *attribute* space. The first point, representing the best value of each of the attributes considered, is the *positive ideal solution* (PIS), while the other point,

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[1] Deductive reasoning moves from the more general to the more specific. The researcher in this case creates a hypothesis based on already existing knowledge about a particular topic and then empirically investigates the validity of this knowledge. It is the process of reasoning from one or more statements (premises) to reach a logically certain conclusion.

[2] The research in the form of a meta-study follows from the initial idea behind meta-ethnography due to (Noblit & Hare, 1988).

representing the worst values of each of the attributes considered, is the *negative ideal solution* (NIS). The attractiveness (relative) of each region can then be judged by its *proximities* to each of these preference poles.

Box 1

TOPSIS Algorithm

1. First, normalization of X is done by dividing each element of a particular column by the positive square root of the sum of squares of all the elements in it. The normalized element for the i^{th} row (region) and the j^{th} column (criterion) is thus:
   $$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$$
2. Next the weighted normalized decision matrix (V) is constructed by multiplying each element (r_{ij}) of the normalized decision matrix with its associated weight w_j, i.e., $(V) = \left[(v_{ij})_{n\times m}\right]$, where $v_{ij} = r_{ij} \times w_j$; $\sum w_j=1$
3. The positive ideal solution (PIS), an m-dimensional (row) vector, A^+ , is found by maximizing each benefit criterion and minimizing each cost criterion. Let J be the set of benefit attributes and J' , the set of cost attributes.
   Then, $A^+ = \{v_1^+, v_2^+, v_3^+, \ldots, v_m^+\}$, where $v_j^+ = \{\max_i v_{ij}, j \in J : \min_i v_{ij}, j \in J'\}$
4. The negative ideal solution (NIS), another m-dimensional (row) vector, A^- , is found by minimizing each benefit criteria and maximizing each cost criteria.
   Thus, $A^- = \{v_1^-, v_2^-, v_3^-, \ldots, v_m^-\}$, where $v_j^- = \{\max_i v_{ij}, j \in J' : \min_i v_{ij}, j \in J\}$;
5. The distance of each DMU from PIS, S_i^+, is found in the multidimensional attribute space by using the Mahalanobis Distance Function as:
   $S_i^+ = (v_i - A^+)\Delta^T\Sigma^{-1}\Delta(v_i - A^+)^T$; $\left\{v_i = (v_{ij})_{j=1(1)m}\right\}$,where Δ , a diagonal matrix, is formed of weights (w_j) and Σ is the variance-covariance matrix of the normalized data matrix in (1), and v_i is the i-th row vector of the matrix V.
   The distance of each DMU from the NIS, S_i^- , is similarly found as:
   $$S_i^- = (v_i - A^-)\Delta^T\Sigma^{-1}\Delta(v_i - A^-)^T$$
6. An index of "relative closeness" to the ideal solution (PIS) is calculated as:
   $$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-} ; 0 \le C_i^+ \le 1 , i = 1(1)n$$

In terms of each benefit (J) and cost (J') criteria if the i^{th} region is the best, $v_i = A^+$ and thus $S_i^+ = 0$ which implies $C_i^+ = 1$.

On the other hand, if the i^{th} region is the worst in terms of each of the attributes $(J \;\&\; J')$, then $v_i = A^-$ and thus $S_i^- = 0$ which implies $C_i^+ = 0$.

Select Empirical Literature

As far as the locational determinants of FDI are concerned, plenty of studies have been made on the inter-country differences in the inflows of FDI (Wei, 2000; Habib & Zurawicki, 2002; Globerman & Shapiro, 2003; Blonigen & Piger, 2011; Walsh & Yu, 2010; Blonigen, 2005). This study attempts to integrate the most accepted and significant location determinants, as presented in *Box 2*.

Box 2
Synthesis of Decisive Determinants of FDI Inflows

Determinant	Sample	Proxy	Method	Sign[3]	Authors
Market Size	Latin America (12 Countries)	GDP Per Capita	Multivariate Regression	+	Tuman & Emmart (1999)
	80 Developing Countries	GNP Per Capita	Multivariate Regression	+	Schneider & Frey (1985)
	BRICS	GDP	Panel Data Regression	+	Vijayakumar, Sridharan, & Rao (2010)
	Greek Regions	Population Potential Index	Multivariate Regression	+	Petrakou (2013)
Infrastructure	BRICS	Infrastructure Index	Panel Data Regression	+	Vijayakumar, Sridharan, & Rao (2010)
	33 African Countries	Length of Paved Roads Per Km^2 Area	Panel Data Regression	+	Khadaroo & Seetanath (2010)
	71 Developing Countries	No. of Phone Lines Per 1000	Multivariate Regression	+	Asiedu E. (2002)

[3] (+) indicates positive and significant relationship; (-) indicates negative and significant relationship; (0) indicates insignificant relationship.

		People			
	Eastern Provinces of China	Length of Highway and Railway per Km^2 of Provincial Land Mass	OLS Regression	+	Helldin (2007)
Investment Incentives	16 SSA Countries	Tax Holiday	Multivariate Regression	0	Cleeve (2008)
	16 SSA Countries	Tax Concession	Multivariate Regression	0	Cleeve (2008)
	16 SSA Countries	Repatriation of Profits	Multivariate Regression	0	Cleeve (2008)
	49 LDCs	Corporate Taxation	Multivariate Regression	-	Gastanaga, Nugent, & Pashamova, (1998)
	42 Countries	Corporate Taxation	Panel Data Regression	0	Wheeler & Moody (1992)
	49 Host Countries	Tax on Foreign Corporations	Multivariate Regression	-	Wei (2000)
Production Cost	80 Developing Countries	Wage Cost Per Worker (Monthly in US$)	Multivariate Regression	-	Schneider & Frey (1985)
	Eastern Provinces of China	Average Annual Wage In Manufacturing Industry (Yuan)	Multivariate Regression	+/-	Helldin (2007)
	42 Countries	Average Hourly Wage In Manufacturing	Panel Data Regression	+	Wheeler & Mody (1992)
Human Capital	32 Emerging Economies	Adult Literacy Rate	Composite Index of FDI Attractiveness	+	Dalsgaard (2013)
	16 SSA Countries	Illiteracy Rate (Adult)	Multivariate Regression		Cleeve (2008)
Agglomeration Effect	Chinese Provinces	Natural Resource	Arellano-Bond Dynamic Panel Generalised	+	Boermans & Zhang (2011)

			Method of Moments (GMM)		
	Transition Economies	FDI Stock Per-Capita	GMM Estimation	+	Kinoshita & Campos (2002)
	Emerging economies of Latin America and Asia	Neighbouring Economy's FDI	Spatial Modelling	+ (for Latin America)	Orr (2008)
	68 Russian Regions	Past FDI Inflows	Spatial Regression Technique	+	Buccellato & Santangelo, (2009)
	African Countries	Past FDI Inflows	Panel Data Regression	+	Anyanwu (2011)

Brief Discussion about the Variables

Infrastructure

Availability of quality infrastructure, particularly of transportation and telecommunications, is an important determinant of FDI. A good transportation system facilitates access to inputs and minimizes the cost of distribution of the finished products as well. The previous literature has shown the positive impact of infrastructure on FDI inflows (Wheeler & Mody, 1992; Kumar, 1994; Loree & Guisinger, 1995; Asiedu, 2002). A region having a good road and rail route network is likely to attract more FDI inflows compared with one having a poorer network of the same. Road (Rail) Route Density, defined as Total Road (Rail) Route length divided by the Geographical Area of a region, has been taken as a determinant of FDI inflows in this study.

FDI which comes mainly in the service sector requires uninterrupted supply of power. It does not depend too much on physical communicational infrastructure (like rail or road) but heavily on energy available in a region. *Availability of electricity* is thus an important determinant of FDI; the states with serious power shortages will receive little FDI inflows[4]. As it is always difficult to make any qualitative assessments, the quantities of infrastructural variables are in general supposed to be representative of their qualities as well. Another difficulty in dealing with this variable (infrastructure) is the complexity and *multidimensionality* inherent in it. It is to be pointed out; in the present context we are considering only transport and electricity[5] and not communication infrastructure (e.g. phone lines and broadband internet connectivity).

Labour conditions

Investments flow into regions having abundant supply of cheap but efficient labour. According to Dunning (1998), foreign firms who are completely unaware of the quality of labour consider higher wage as a proxy for the skill of labour. Thus a higher-wage region might also attract a higher level of foreign

[4] See for example Ghosh & De (2005).

[5] See for example a recent study by Buccellato & Santangelo (2009).

investment as shown in studies conducted by Head, Ries, & Swenson (1999), Thiran & Yamawaki (1995), Guimaraes, Figueiredo, & Woodward (2000) and Pelegrín (2003). The possible impact of the level of wages in effecting FDI inflows is thus ambiguous. As a cost of labour, the lower the wage rate, the higher should be the level of inflows; as a proxy for the skill of labour, though, the relationship is exactly the opposite.

The present study uses literacy rate and wage rate as factors representing the labour conditions of a specific region. The relevance of wage costs, on which previous literature has focused, is "highly sensitive to small alterations in the conditioning information set" in cross-country studies as shown in the Extreme Bounds Analysis of Chakrabarti (2001). But even if higher wages discourage (vertical) FDI flows at the host country level, location choices by foreign investors within the low-wage countries such as India are hardly to be affected as the regional gaps in wages are small compared with the country-specific gaps, i.e. between the host and foreign countries.

Stock of FDI

The stock of FDI, i.e., cumulative sum of year-wise FDI inflows, is the most important factor causing the regional clustering/concentration in the distribution of FDI. There is a tendency of industries to concentrate in areas where a set-up already exists. This is referred to as the *agglomeration effect* in the literature. *Agglomeration economies* emerge when there are some positive externalities in collocating near other economic units because of the presence of knowledge spillovers, specialised labour markets and supplier networks (Krugman, 1991). According to He (2002), foreign firms, with an intention to minimize *information costs* and other uncertainty of investments, prefer regions where the level of investment is already high. Higher stocks (of FDI) bode well as a signal of profitability for the respective regions to the prospective (foreign) investors. New firms also get external benefits in the form of good supply of inputs from these regions (where FDI stock is very high) because of the pre-existing industrial set-up built up by other firms. Also products produced by some firms can be used as inputs by some other firms. A -pre-existing set-up also helps new firms escape the huge fixed cost of setting up infrastructure and reap the benefits of increasing returns to scale. The theory of "learning curve"[6] also suggests that it is beneficial for existing firms to invest in regions with higher per-capita FDI stocks.

Market Size

While determining the suitable region for investment, foreign firms consider market size as one important determinant. A large market, on the one hand, ensures larger demand for the products, and on the other, easy and larger supply of inputs of production. Now, foreign firms who are unaware of the size of market consider state domestic product as a representative of market size. A higher state domestic product in a specific region implies a larger market in that region. Also, as domestic investment is high in that market, it gives the signal that investment is profitable there[7]. In this context we have to remember that by large market we mean where investment or business is large. A market which is large by area is not helpful for

[6] "Learning Curve" relates to the amount of inputs needed by a firm to produce each unit of output to its cumulative output.

[7] Kravis & Lipsey (1982) found a positive relationship between the market size in host nations and the location decision of US multinationals. Anitha (2012) showed the same thing in the context of India.

this purpose. Now, to eliminate the effect of size of the area, we have considered per capita net state domestic product (NSDP) as an explanatory variable influencing the inflows of FDI.

Policy environment

It is essential for states to formulate appropriate policy measures so as to attract investors. The previous literature shows the impact of government policies on FDI inflows into a host country (Blomstrom & Kokko, 2003; Schneider & Frey, 1985; Loree & Guisinger, 1995; Taylor, 2000; Kumar, 2002b). States generally do give many types of incentives to attract investors in an effort to outsmart the others (states). Tax exemption, simpler tax structure, and single-window system for obtaining licence or other permissions as required before the start of business are some of the incentives offered by the states from time to time. We have taken the state tax rate as an explanatory variable for representing policy environment in a particular region. In the absence of requisite data, however, we have used state's own tax revenue as a proportion of its NSDP as a proxy of its tax rate. The intuition is that own tax revenue will be higher (lower), the higher (lower) the tax rate.

There are other factors too, viz., political stability of a state government and the Centre-state financial relationship, in particular. The absence of a strong and stable government as well as a sound federal structure renders a region more vulnerable to risks, which reduce the incentive to invest to a great extent (Basant & Saha, 2005)[8].

It may be pointed out that the theoretical framework and previous empirical findings have provided a sound starting point in the selection of the data and choice of proxies to be used subsequently in constructing the composite FDI attractiveness index for a state/region.

Selection of Proxies

The selection of proxies in the present study has essentially been based on the statistical significance of determinants as found in the previous empirical findings (refer *Box 2*) as well as on their appropriateness and accessibility of the requisite data for the purpose of constructing a composite index. It is essential that the index contain proxies that are based on the same selection criteria, to ensure consistency in the measurement of the FDI attractiveness index (OECD, 2008; CSLS, 2012). The rankings based on individual proxies should thus bear a one-to-one correspondence with the composite FDI ranking.

Box 3
Proxies Selected for the Study

Type of Factor	Proxy	Description	Type of Attribute[9]	Expected Sign
Market Size	Per-Capita NSDP	Net State Domestic Product at Factor Cost/Population Size	Benefit	+
Infrastructure	Road Route Density	Total Length of Roads per 1,000 Square Kilometre of Geographical Area	Benefit	+

[8] But because of the lack of data we have not considered risk factor as an explanatory variable in the empirical analysis of this paper.

[9] While an enhancement in the provision of "Benefit" attributes leads to betterment in the position of a region that for the "Cost" attributes leads to deterioration in the same (see the Section before *Box 1*).

	Rail Route Density	Total Route Length per 1,000 Square Kilometre of Geographical Area	Benefit	+
	Availability of Energy	Total Availability of Electricity in a State (GWH)	Benefit	+
Labour Conditions	Wages per Worker	Labour Costs Per Man-day Worked on Wages/Salaries	Cost	-
	Literacy Rate	Proportion of Literate Population Aged Seven Years and Above	Benefit	+
Policy Environment	State's Own Tax Revenue as per cent of NSDP	State Tax Revenue ≡ Own Tax Revenue (A) + Share in Central Tax Revenue (B). A ≡ VAT + State Excise Duties + Commodity-specific Taxes + Others	Cost	-
Agglomeration Effect	Per Capita FDI Stock	One-period Lagged Value of Cumulative FDI Inflows	Benefit	+

The positive (negative) ideal solution is found by maximizing (minimizing) the benefit attributes and minimizing (maximizing) the cost attributes (*Box 3*). The attractiveness score of a state/region is found by observing its distance in reference to these poles (PIS and NIS) using the TOPSIS algorithm (*Box 1*).

3. Data and Results

A state-level dataset of India covering 31 states and Union territories has been considered for the empirical analysis carried out in this paper[10]. This is a case study to prove the effectiveness of the composite FDI attractive scores. The states have been classified into 16 groups so as to correspond to the classification of groups used by the regional offices of the Reserve Bank of India (RBI) when it publishes its region-wise data on FDI inflows. (The present study has used these region-wise data of the RBI.)

Accordingly, the region of Mumbai covers Maharashtra, Dadra & Nagar Haveli and Daman & Diu; Chennai covers Tamil Nadu, and Pondicherry; Kochi covers Kerala, and Lakshadweep; Kanpur covers Uttar Pradesh, and Uttarakhand; Patna includes Bihar, and Jharkhand; Bhopal includes Madhya Pradesh, and Chhattisgarh; Gauhati covers Assam, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland and Tripura; Kolkata covers West Bengal, Sikkim, and Andaman & Nicobar Islands; Chandigarh covers

[10] Data on all the variables not being available for all the years and due to postponement of the publication of the new census data (which was scheduled to be published in 2020) the latest census data available to us being that of 2010, we have restricted our data set for the period: 2001-02 to 2012-13.

Chandigarh, Punjab, Haryana, and Himachal Pradesh; and New Delhi covers Delhi, part of Uttar Pradesh, and Haryana. State-specific data are however available for Gujarat, Karnataka, Goa, Andhra Pradesh, Orissa and Rajasthan; the regional correspondence to these states being respectively, Ahmedabad, Bangalore, Panaji, Hyderabad, Bhubaneshwar, and Jaipur.

The data on the explanatory variables (*Box 3*) have been obtained from multiple sources. Information on per capita income has been obtained from the National Accounts Statistics (NAS) and the Handbook of Statistics on the Indian Economy published by the Central Statistics Office (CSO) of the Government of India (GoI) and the RBI, respectively. The data on road statistics are taken from the Ministry of Road Transport and Highways (GoI); the data related to rail networks have been compiled from "Annual Statistical Statements" published by the Ministry of Railways, Railway Board (GoI). The data on the availability of electricity have been collected from Central Electricity Authority Ministry of Power, Government of India. The data on daily wages per worker as collected from *www.indiastat.com* have been compiled from the dataset released by the Ministry of Labour and Employment, (GoI). The data on literacy rates and population have been worked out from the Census of India. The data on tax revenue of the Indian states have been compiled from various issues of the RBI Reports on 'State Finances: A Study of Budgets'.

The year-wise FDI attractiveness scores for each region have been computed by applying the TOPSIS algorithm (*Box 1*). The scores are however dependent on the relative weights which investors accord to different attributes while taking a decision on FDI. In the absence of any subjective information about the preference pattern of investors, we apply the concept of "entropy" to estimate the year-wise attribute-specific weights[11]. The idea is essentially built on the assumption that a criterion is less important if the variation in regional shares (in the aggregate value over all regions) is less for that criterion. Now by setting the weight equal to unity for a particular attribute (and zero for the rest) we get the regional FDI attractiveness scores based on a single criterion only. For example, if the maximum possible weight of one is attached to per-capita NSDP and zero to the rest, the TOPSIS scores (rankings) coincide with normalized scores (ranking) with respect to per-capita NSDP.

As the results (TOPSIS Scores)[12] indicate, New Delhi consistently surpasses the other regions on potential to attract FDI. While Panaji comes up second in the list, the third and fourth positions are occupied alternately by Mumbai and Kochi. Expectedly, the scores turn out to be extremely low for Gauhati, Patna, and Jaipur. As has been discussed earlier, the higher the score, the higher should be the actual inflows to a specific region. It may be noted here that the TOPSIS rankings (*Table 1*) do not simply reflect the *rank aggregations* across the attribute-specific rankings. The scores rather correspond to their relative closeness to the ideal solution (PIS) based on the Mahalanobis Distance Metric (Mahalanobis, 1936). Here application of a Mahalanobis distance function as against the normal Euclidean Distance Metric is essentially meant to take care of the inherent correlation structure in the data matrix (X). This means that the results will

[11] The entropy algorithm is given in Appendix A1.

[12] TOPSIS Scores are not shown here. Ranking of regions based on score is shown in Table 1.

converge in case the variance-covariance structure of the underlying data matrix collapses to an identity matrix[13].

Table 1
Year-wise Rankings based on TOPSIS Scores

RBI Regions	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
New Delhi	1	1	1	1	1	1	1	1	1	1	1	1
Panaji	2	2	2	2	2	2	2	2	2	2	2	2
Kochi	3	3	3	3	3	3	3	3	4	4	4	4
Chennai	4	4	4	4	4	4	5	6	6	6	6	6
Mumbai	5	5	5	5	6	6	4	4	3	3	3	3
Ahmedabad	6	6	6	7	8	8	8	8	8	8	8	8
Bangalore	7	7	7	6	7	7	7	7	7	7	7	7
Kolkata	8	8	8	8	5	5	6	5	5	5	5	5
Bhubaneshwar	9	9	9	9	9	9	9	10	11	12	12	12
Chandigarh	10	10	10	10	10	10	10	11	9	9	9	9
Hyderabad	11	11	11	11	11	11	11	9	10	10	10	10
Kanpur	12	12	12	12	12	12	12	12	12	11	11	11
Bhopal	13	14	14	14	14	14	15	15	15	16	16	15
Patna	14	13	13	13	13	13	13	13	13	13	13	13
Jaipur	15	15	15	16	16	16	16	16	16	15	15	16
Gauhati	16	16	16	15	15	15	14	14	14	14	14	14

The correlation analysis applied between the regional scores (rankings) based on actual per-capita FDI inflows and the composite FDI attractiveness scores (and rankings thereof; refer *Table 1*) gives the following results:

i) The average Spearman Rank Correlation coefficient is significantly high (0.8) at 1 per cent level of significance.

ii) The two sets of rankings register an exact tie almost 20 per cent of the times.

Further, actual scores (rankings) are compared with attribute-specific scores (rankings).

i) As regards the stock of FDI, the rank correlation coefficient comes out to be significantly higher compared with (i) above.

ii) The correlation coefficients are found to be positive and statistically significant for road density and availability of electricity.

iii) The coefficients turn out to be negative for tax rate and positive for per-capita NSDP. For the rest of the variables, the correlation coefficients are found to be statistically non-significant.

The above results suggest that while all the proxies in *Box 3* are potential determinants of FDI, investors have preference for some specific factors, maximum importance being given to per-capita stock of FDI and the basic infrastructural set-up.

[13] A brief discussion on the concept of the Mahalanobis distance function is presented in Appendix A2.

4. Conclusion

The paper has proposed a methodology of deriving a composite index of FDI attractiveness index. The method is contingent upon the choice of attribute-specific weights while aggregating the individual attributes for the construction of the composite index. The specific weighting methodology adopted in this paper is the procedure of entropy based weighting. Specifically, we use the Shannonian concept of entropy $(H(X))$; weights are distributed among the attributes taking into account the differences in the magnitudes of information disseminated from each of them (attributes), the entropy state function being simply the amount of information that would be needed to specify the full microstate of the system. The novelty of the present methodology is that if the weight assigned to a specific attribute (determinant) is made equal to one, thus assigning zero weights to the rest of the attributes; it leads us to a ranking based on the specific attribute only. By varying the weights assigned to a specific factor, the relative importance of the same vis-à-vis the composite index can be assessed which has important policy implications. The difference in the realized values of FDI inflows can thus be attributed to specific factors/determinants which can thus be controlled so as to target inflows to specific regions.

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Appendix A1: Estimation of Entropy Weights

In the Shannonian Concept of Entropy, weights are distributed among the attributes in proportion to the magnitudes of the *information* disseminated from each of them (attributes), the *entropy state function* being simply the amount of information that would be needed to specify the full microstate of the system. Estimation of weights involves the following steps.

1. X is normalized so as to scale down the attributes between zero and one. The normalization rules are: $y_{ij} = \frac{(x_{ij})-(x_{ij})_{min}}{(x_{ij})_{max}-(x_{ij})_{min}}$ (for benefit attributes) & $y_{ij} = \frac{(x_{ij})_{max}-(x_{ij})}{(x_{ij})_{max}-(x_{ij})_{min}}$ (for cost attributes)
2. From the transformed data matrix $Y = \left[(y_{ij})\right]$, the relative scores of regions (across proxies) are found as $a_{ij} = \frac{y_{ij}}{\sum_i y_{ij}}$
3. The amount of decision information contained in $A = \left[(a_{ij})\right]$ and emitted from each of the proxies is measured by the entropy value: $e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} a_{ij} \ln a_{ij};\ 0 \le e_j \le 1$
4. The degree of divergence (d_j) of the average intrinsic information contained in each criterion is measured as: $d_j = 1 - e_j$ The more divergent the relative scores $\left(a_{ij},\ \forall\, i = 1(1)n\right)$ for the criterion j, the higher the corresponding d_j and the more important the specific criterion. This essentially means that a criterion (proxy) is less important if the variation in the relative scores (a_{ij}) over the regions is less for that criterion (proxy).
5. The weights for each criterion are given by: $w_j = \frac{d_j}{\sum_{k=1}^{m} d_k}$

Appendix A2: Mahalanobis Distance Function

Mahalanobis distance is used to calculate the distance between two Centroids (Legendre & Legendre, 1998) allowing for oblique positioning of an "elliptic envelope" within a multidimensional attribute space (Farber & Kadmon, 2003). The idea is that the distance between similar objects should be relatively smaller than that between dissimilar ones.

Mathematically, the Mahalanobis distance between a vector x and a set S of vectors (matrix) is defined as:

$D^2 = (x - m)^T C^{-1}(x - m)$;

m being the mean vector and C, the covariance matrix of S (Clark, Dunn, & Smith, 1993). The rows of S stand for observations (regions) and the columns for the status of attributes (proxies). The vector m represents the optimum conditions and x the status of attributes for any particular observation (region). When the Variance-Covariance matrix is the Identity matrix, the Mahalanobis distance reduces to the usual Euclidean distance.