Research Productivity in Management Schools of India: A Directional Benefit-of-Doubt Model Analysis

Biresh K. Sahoo[a], **Ramadhar Singh**[b], **Bineet Mishra**[c], **Krithiga Sankaran**[d]

[a] Xavier Institute of Management, Xavier University, Xavier Square, Bhubaneswar 751013, India
e-mail: biresh@ximb.ac.in

[b] Indian Institute of Management Bangalore, Bannerghatta Road, Bangalore 560076, India
e-mail: ramadhar@iimb.ernet.in

[c] Xavier Institute of Management, Xavier University, Xavier Square, Bhubaneswar 751013, India
e-mail: bineet1986@gmail.com

[d] Indian Institute of Management, Bannerghatta Road, Bangalore 560076, India
e-mail: krithiga.sankaran@iimb.ernet.in

Abstract

Given the growing emphasis on research productivity in management schools in India, the present authors developed a composite indicator (CI) of research productivity, using the directional benefit-of-doubt (D-BOD) model, which can serve as a valuable index of research productivity in India. Specifically, we examined overall research productivity of the schools and the faculty members during the 1968-2014 and 2004-2014 periods in a manner never done before. There are four key findings. First, the relative weights of the journal tier, total citations, impact factor, author *h*-index, number of papers, and journal *h*-index varied from high to low in order for estimating the CI of a faculty member. Second, both public and private schools were similar in research productivity. However, faculty members at the Indian Institutes of Technology (IITs) outperformed those at the Indian Institutes of Management (IIMs). Third, faculty members who had their doctoral degrees from foreign, relative to Indian, schools were more productive. Among those trained in India, alumni of IITs, compared to those of IIMs, were more productive. Finally, IIMs at Ahmedabad and Bangalore and the Indian School of Business, Hyderabad have seemingly more superstars than other schools among the top 5% researchers during 2004-2014. These findings indicate a shift in the priority from mere training of managers to generating impactful knowledge by at least two of the three established public schools, and call attention to improving the quality of doctoral training in India in general and IIMs in particular. Suggestions for improving research productivity are also offered.

Key words: Data envelopment analysis; Research productivity; Composite indicator; Business schools

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1. Introduction

India has recently been aiming to become a hub of knowledge. Highlighting the need for according the highest priority to the science, technology, and innovation in transforming the nation, Prime Minister Narendra Modi announced at the 102nd Indian Science Congress that the Government of India (GOI) would provide the scientific community and universities with an atmosphere conducive to pursue world-class research [1]. The GOI has also been developing a strong culture of collaboration between institutions and across disciplines to avail the cross-functional advantage of expertise, development, and innovation. Put simply, the GOI is favorably inclined toward driving institutions of higher learning including business management schools to undertake world class research.

International schools have been recently entering into research collaboration with Indian institutions as well. The All India Council of Technical Education (AICTE), for example, has now come up with the guidelines on how a foreign university can collaborate with the Indian academia in research [2]. Global higher education brands have already opened research centers in India to tap the research opportunities that India offers [3]. While the Harvard Business School has a research center in Mumbai, the University of Chicago and Deakin University have similar research centers in New Delhi. Such powerhouse research centers supposedly aim at engaging colleges, research institutes, business entities, and the GOI offices to work on different projects. These developments highlight the growing importance of business research and of India as an exciting site for such research.

Despite the growing emphasis on research in management schools and other academic institutions of higher learning in India, management schools have not yet met world standards in research. For example, the Indian Institutes of Management (IIMs), the Indian Institutes of Technology (IITs), and the Central Universities (CUs)--the premier institutions established by GOI--did not make to the list of top 100 productive schools across three successive surveys [4,5,6]. Consequently, the Ministry of the Human Resource Development (MHRD) of GOI sponsored the PanIIM Conferences at Goa in 2013 and at Kozhikode in 2014. Unfortunately, the Goa Conference found no paper worthy of an award, confirming the poor quality of research [7]. Thus, research productivity of the management institutions continues to be a matter of vexing concern for academics and policy-makers in India. Given the continued interest in research productivity of management scholars in India, we set out to develop a composite index of research productivity that could gauge how creative and productive faculty members of management schools have been over the years.

1.1 Research in business management schools in India: current debates

In 2011, the then Environment Minister for India kicked up a controversy by commenting that faculty members at the premier universities, including the IIMs and IITs, were neither world-class nor worthwhile with respects to creativity and research [8]. Countering this comment, the then Human Resource Development Minister, however, attributed the poor research productivity in IITs and IIMs more to limited resources, low priority to research, and limited research support rather than to poor quality of faculty members themselves [9].

Using the ISI Web of Science database, Kumar [10] found only 132 author counts (108 unique articles) by scholars affiliated with Indian management schools during 1990-2009. To provide a perspective on how low this Indian productivity might be, he contrasted the productivity of around 5 articles per year for the entire India with the productivity of the business school at the Hong Kong University of Science and Technology (HKUST), China, whose 100 plus faculty members had produced over 30 articles annually and of the Wharton Business School, University of Pennsylvania, Philadelphia, USA, whose 200 plus faculty members had produced about twice as many number of articles annually as HKUST. A follow up editorial on 'Publish or Perish' in the Economic Times [11] also reiterated such a need for producing high quality research from Indian business schools (B-Schools).

One response to the foregoing suggestions has been seemingly defensive: Indian scholars should study Indian problems, using indigenous methods, and publish in Indian journals. Pressure to publish in world class journals can unfortunately result in imitation instead of generation of original thoughts and methods. As Khatri et al. [12] argued, publishing in international journals would require writing for their audiences and contexts using their theories and methods, which may not augur well the Indian management research. Another equally defensive response is that international journals are disinterested in publishing Indian data. Refuting this possibility, however, Singh [13] recently argued for sloppy research (i.e., issues selected, techniques employed, unclear writing, etc.) by Indian faculty as a factor in low record of international publications by faculty members of B-Schools in India.

Of the suggestions offered to improve quality of management research in India, two are notable. One is shift in emphasis from teaching to research. That is, B-Schools should make research mandatory, enhance research capabilities, hire more research-trained faculty, and provide those faculty members who publish in international journals with financial incentives [14]. Another is a culture of collaboration in research where like Scandinavian B-Schools, management schools in India should initiate research collaboration with foreign schools of repute and allocate adequate funds for bringing in research faculty

from abroad [14]. Consistent with these suggestions, B-Schools in India have already made several interventions to improve research productivity. For example, the premier schools in India have started emphasizing quality research to improve the rankings of B-Schools in India among their global counterparts [15]. Further, the tenure and promotion of faculty members depend more on research productivity now than ever before [16,17].

1.2 Measuring research productivity of a business school

A well-known indicator of research is the number of publications in peer-reviewed journals that facilitate dissemination of knowledge among management scholars and practitioners. In fact, academic institutions are nowadays adjudged by their publications in reputed journals, and there has been an increasing proliferation of the rankings, listings, and productivity indicators of schools and universities in recent years. These rankings have drawn the attention of not only the associations such as the Association of Business Schools (ABS) and the Association to Advance Collegiate Schools of Business (AACSB), for example, but also the dominant industry players such as Thomson Reuters' Web of Science, Elsevier's Scopus, and Google Scholar.

Most areas of management[1] analyze research productivity in terms of either the reputation of an author or the quality of the journal in which an article was published. The former is usually judged by an author's total number of published papers [18-20], h-index[2] [18, 20-22], and the number of citations of that author's publications [18]. The quality of journals is often judged by its h-index[3] [22], tiering[4], and impact factor (IF)[5] [23-27]. Each such indicator taken in isolation has its own strengths and weaknesses in gauging the overall scholarly contribution of a researcher (see. e.g., Mingers and Leydesdorff [28] for a detailed discussion on the strengths and weaknesses of each of these indicators). Some academic researchers have even objected to this counting in science and termed it as 'mismeasurement of science' [29].

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[1] Such discipline-based studies have been conducted in the past in areas such accounting, business, finance, management, marketing, management information systems, operations research /management science [18].

[2] A scholar has index h if h of his/her n papers have at least h citations each and the remaining $(n-h)$ papers have at most h citations each. This index measures the scientific productivity and impact of a scholar's research.

[3] The h-index of a journal expresses the number of its articles (h) that have received at least h citations. It quantifies the journal's scientific productivity and scientific impact.

[4] The journals are classified into four tiers (Tiers: 1-4), with Tier 1 being most important and Tier 4 the least important. This tier classification is based on the lists by the National University of Singapore and the Association of Business Schools (ABS), UK.

[5] IF measures the scientific impact of an average article published in a journal. It is computed considering the number of citations received in the given year by an average article published in the given journal within a pre-defined number of preceding years.

Research productivity has previously been judged along multiple criteria as well. We found two obvious shortcomings with such studies. First, research productivity judged from single indicator, when there are multiple overlapping indicators, might be misleading. Second, there is a growing trend of publishing an article with multiple authors. For example, the present second author, who published single-authored articles in 1970s [30,31], 1980s [32,33] and 1990s [34-36], has recently been publishing articles authored with 8 to 10 colleagues and/or students to train these younger generation of scholars [37,38]. Here, assigning equal importance or weight to the contribution of each individual author in such cases might erroneously underestimate the productivity of first author and overestimate the contributions of the co-authors. On the contrary, there are several seemingly well-published faculty members in India who do not even have a single-authored paper. We are afraid that they might be merely collecting the data for well-known scholars abroad to get co-authorship in tier-1 publications. Assigning equal importance or weight to the contribution of each individual author in such cases might erroneously overestimate the productivity of co-authors from India. Given these concerns, we decided to aggregate multiple non-commensurate indicators and weight one's contribution to an article by the order of authorships. Although we are aware that this might not be a perfect solution prticualarly when authorships go by alphabetical orders of the last names instead of contributions to the article, we believe that our system may be better than non-weighting of the order of authorships.

1.3 Overall productivity

A comprehensive measure of the overall research productivity required us to integrate multiple non-commensurate indicators into a single composite index (CI). While developing such CI, we were as aware as were other recent scholars (cf. [39,40]) that all the indicators might not be equally diagnostic of research productivity. To be meaningful, the CI requires setting of unknown weights for the indicators used, depending upon their relative importance. To us, the weight of an indicator should reflect on the priority given to it by the individual researcher contingent upon his or her career and aspiration (i.e., age, education, experience, and positions sought, etc.). If weights fail to capture the priorities given to one's career strategy, the resulting CI of research productivity might become questionable in terms of its unintended consequence of a skewed scholarship for younger more than senior faculty members.

We considered the data envelopment analysis (DEA) and the econometric approach as two ways of endogenously generating unknown weights (cf. [41-43]). Because of the identification of an efficient frontier, the DEA seemed to have an advantage over the traditional econometric approach in generating

the impartial benefit of the doubt (BOD) weighting [44].[6] That is, if a researcher has high productivity according to one indicator of *h*-index, then the relative weight of his *h*-index should be correspondingly high. Since the CI estimate from the DEA measures the *maximum* productivity performance of a researcher, high research productivity in the BOD weighting implies high priority to the career strategy.

To overcome the aforementioned two problems, we employed the DEA model to comprehensively gauge the research productivity of every scholar. We used six indicators. Whereas the first three pertained to the author: (1) *h*-index scores (I_1), (2) total citations (I_2), and (3) number of publications (I_3), the last three pertained to the journal: (4) *h*-index scores (I_4), (5) tier scores (I_5), and (6) Impact Factor (IF) scores (I_6). We took the *h*-index and the IF scores of the various journals from the *Scopus*--a citation database by the Elsevier--which has a much broader coverage of journals than the alternative Journal Citations Reports (JCR) of the Thompson Reuter.

Nevertheless, we realized that the sole reliance on citations in journal rankings by the *Scopus* may not always be accurate. For example, an otherwise important work that is casually dismissed as common knowledge may not get cited at all. Authors working on niche areas get cited less [30]. Worse, citation counts may at times be more a fashion within the academic community than a true indicator of the impact of the journal [47-50]. Citation-based analyses can also be biased due to selective citations or self- and mutual citations which render the association between the quality of a journal and that of an individual article in it rather uninformative [50-52]. Despite these reservations, these citation-based indicators continue to be viewed as the valid representatives of the quality of journals in the contemporary literature. Thus, we included citations as one of the six indicators of research productivity in our DEA model.

Scholars around world in general and India in particular have been skeptical of the coverage by the Scopus. In particular, the Scopus has been accused of excluding the citations from books and non-traditional sources, such as web sites, dissertations, monographs, chapters in the edited volumes, open-access online journals, and/or the proceedings of important conferences [53]. In response to such concerns, we selected publications included in the ranking list of the National University of Singapore

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[6] DEA can also be interpreted as embedding a feature of 'appreciative democratic voice' in evaluating decision making units. This means that each and every decision making unit is given an opportunity to evaluate himself/herself in a manner that will be most favorable to him/her. It thus resonates and accentuates a philosophy of favoring each and every decision making unit [45]. However, interested readers may refer to Dyson et al. [46] on an excellent discussion, on some of the pitfalls usually faced by researchers in several application areas, and then on the possible protocols to be followed to avoid those pitfalls.

(NUS). For the sake of fairness and comprehensiveness, we further considered publications in all journals listed in the Scopus, ABS, and NUS databases. To enhance accuracy, we further relied on the author's *h*-index[7] and the total citations reported in the Google Scholar[8] that covers all sorts of citation from published and unpublished documents. We believe that consideration of Indicators 1 to 3 mitigates some of the concerns of Indian scholars and that of Indicators 4 to 6 gives them due credit for publishing in prime international journals.

Given our directional benefit-of-the-doubt model analysis of the relative weights of six non-commensurate indicators in developing the CI of research productivity of a faculty member, we felt confident that our indices might be psychometrically much better and practically more useful than the alternative estimates for at least four key reasons. First, reliance on the relative weights of individual indicators in estimating the CI is not only a methodological innovation in productivity assessment [59,60] but also an objective check on whether the earlier cited Western rankings had portrayed research productivity in B-Schools of India fairly. Second, the relative weights and the CI can serve as a uniform yardstick for comparisons between performance of B-Schools run and managed by the GOI (i.e., public) and those by the private individuals or groups. For example, IIMs, IITs, and CUs are public institutions; the Indian School of Business (ISB) and Xavier Institute of Management Bhubaneswar (XIMB) are, in contrast, private institutions. Notably, uniform measures can be useful in first testing the *property right* hypothesis that the private firms usually perform better than the public ones [61,62], and then capturing the policy strategies of the top-performing versus not-so performing faculty members in research. Third, academic institutions, industries, foreign collaborators, and students can benefit considerably from our low-cost information in their rather high cost decisions on whom to recruit and retain, where to go for campus recruitments and consult on management issues, whom to collaborate in India, and where to get quality management education. Those interested in academic careers might specifically benefit in choosing a correct school and a suitable supervisor within each school for their doctoral degrees or post-doctoral fellowships in management. Finally, and no less important, the research funding bodies in India (see, e.g., Indian Council of Social Science Research, Indian Council of Agricultural Research, Council of Scientific

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[7] The author's *h*-index score from the Google Scholar will be no less than that from the Scopus since the latter includes citations only from a list of selected journals and a few conference proceedings. See the link <http://www.scimagojr.com/journalrank.php> for the detailed list of journals covered under the Scopus.
[8] Even Google Scholar is not free from criticisms such as inclusion of some non-scholarly citations [54], exclusion of some scholarly journals [55], uneven coverage across different fields of study [56,57], and not performing well for older publications [55]. However, on comparison, the Google Scholar may be perceived as providing a relatively more complete picture of an academics impact than the Web of Science and the Scopus [58].

and Industrial Research) may benefit in their decisions on supporting research projects of a researcher as may the scholars from top global B-Schools in India and abroad in choosing ideal research collaborators from other schools.

To the best of our knowledge, ours is the first attempt toward assessing the state-of-the-art in research productivity in B-Schools of India. We are also the first to come up with CI that seems to be more valid and practical than any of the previously used indices of research productivity. Thus, we believe that developing a comprehensive CI of research productivity in management through the directional benefit-of-the-doubt model analysis will yield valuable information on various productivity drivers (indicators) which will be useful to B-Schools in setting right direction in not only enhancing research productivity in Indian academia but also improving their rankings among their global counterparts.

The remainder of this paper unfolds as follows. Section 2 deals first, with issues and problems in our data collection, and second, with the presentation of relevant data of B-schools in India used to arrive at six indicators. Section 3 first presents the description of BOD models used to estimate CI, then points out the limitations therein, and finally suggests a generalized version of the D-BOD model. While Section 4 deals with the presentation of our results, Section 5 deals with the discussion of the results. Section 6 ends with some suggestions for accelerating research productivity in India.

2. Data collection

Collecting the accurate data on publications by the faculty members of different B-Schools in India was a mammoth task for us. In general, faculty members did not provide the full information on their respective websites (e.g., "a large number of publications in reputed journals"). Of those who reported the titles of the articles and the names of the journals, most of them did not report the orders of authorships (e.g., "coauthored with other professors") either. We faced difficulties in accessing information about the year in which a degree or diploma was conferred as well as the work experiences (e.g., academia, industries, government, etc.) and sabbatical leaves which might be the possible moderators of the link between their quality of doctoral training and subsequent research productivity. Consequently, we searched the individual B-School's webpages, the NUS/ABS/Scopus databases, and the Google Scholar for the top 32 B-Schools in India. We selected these 32 schools as they appear in the ranking lists of top performers by various ranking surveys (*Outlook, the Business World,* and *the Careers360*) over the last five years. The other schools were not selected on the premise that their research contributions were hardly visible. As of February 28, 2015, we found 5,543 publications by 784 faculty members during 1968-69 to 2014-15 listed in the NUS,

ABS, and Scopus ranking lists. Given that the first management publication from India was in 1968-69, we made 1968 as the starting year for the directional benefit-of-the-doubt model analysis reported in this article.

We browsed through the webpages of 784 individual faculty members to collect the data needed for our analyses. In particular, we recorded the number of papers, the names of journals in which papers had appeared along with the volume, issue, and page numbers, and the number of authors of each paper. We then took h-index scores along with total citations from the Google Scholar. Some faculty members had reported these scores on their webpages. For those who did not have pages in the Google Scholar, we searched for citations of their articles one by one to compute their authors' h-index scores. To find out both h-index and IF scores of the journals in which an article had appeared, we visited the SCImago webpage < http://www.scimagojr.com/journalsearch.php>. We considered the two-year IF scores of each journal in 2013.

Finally, we browsed through the ranking lists by the NUS and ABS to identify the tier of the journals. When the two lists differed in the tier of a particular journal, we took the higher of the two. For example, if a journal was in Tier 2 in the NUS list but in Tier 3 in the ABS list, we placed that journal in Tier 2. In calculating the journal tier score, we assigned 20, 10, 5, and 2.5 points to the journals classified as Tiers 1, 2, 3, and 4, respectively. Twenty-two journals which are recognized worldwide as exemplars of excellence within the broader field of business and management including economics had 40 points.

For articles with multiple authors, we came up with an estimate that considered both the number of authors and the orders of authorship. For example, consider a paper by an author o in the journal k in which there are n authors, and the order of the author o under evaluation is i. The weight of the ith order author o was thus $w_i = 2^{n-i} / (2^n - 1)$. The tier score assigned to the author o was $w_i \cdot TP_k$, where TP_k represented the tier points assigned to the journal k. Here $\sum_{i=1}^{n} w_i = 1$. For example, consider a paper in International Journal of Production Research (IJPR) where there are three authors. Here, $k = IJPR$, $n = 3$, and $TP_k = 20$ (as IJPR belongs to Tier 1 and Tier 2 categories in the NUS and the ABS respectively, and we considered the better of the two). If the author o under evaluation is the second author (i.e., $i = 2$), then $w_2 = 2^{3-2} / (2^3 - 1) = 0.2857$, and the tier score assigned the author o is 5.714 (as $w_2 \cdot TP_k = 0.2857 \times 20 = 5.714$). Similarly, the author o's scores with respect to the journal k's h-index and IF were

computed in the same manner. Finally, the author's scores on each of these indicators over all of his or her papers were summed to yield the total score.

It is undoubtedly unfair to compare the research productivity of a younger faculty member with 5-year of experience with a senior one with 40-year of experience. The younger colleague may have 2 publications in Tier 1 journals but the older colleague may have publications in journals of Tiers 1 to 4. To eliminate such bias, we corrected each of these six indicators with the number of years (x) spent in research by every faculty member considered. The best possible way to measure x could have been to subtract from the current year (i.e., 2014-15) the enrolment year in one's doctoral program. Given the difficulty in accessing such data as pointed out earlier, we considered the year of award of the PhD degree as the proxy. In cases where even such information was missing, we considered the year of the first journal publication as a proxy.[9] In this way, we ended up by computing the number of years a researcher o had invested $(x_o) = 2015$ - min {year of PhD degree, year of the first published research paper}.

3. Methodology – Directional benefit-of-doubt model

Before constructing the CI of research productivity, we normalized the individual indicators such that they varied between zero (i.e., 0 = worst performance) and one (i.e., 1 = best performance) in the sample. Let us define J as the set of N researchers / faculty members, i.e., $J = \{1, 2, ..., N\}$. The normalized counterpart of rth indicator $\left(r \in R = \{1, 2, ..., 6\}\right)$ for a faculty member j, $j \in J$ was computed as:

$$I_{rj}^n = \frac{I_{rj} - \underline{I}_r}{\overline{I}_r - \underline{I}_r},$$ (1)

where $\overline{I}_r = \max_{j \in J} \{I_{rj}\}$ and $\underline{I}_r = \min_{j \in J} \{y_{rj}\}$ for all $r \in R$.

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[9] It is likely that a faculty member has received his/her PhD degree much earlier than the year in which his/her first research paper appeared, in which case the year-adjusted indicators are unduly overestimated. However, since no other alternative was available, we continued with the first paper appearing year as the proxy for the starting year of research activity.

In order to construct the CI of research productivity, we used a linear weighted sum of the six normalized indicators. Using I_{rj}^{n} to denote the rth normalized indicator by the jth faculty member, the CI of research productivity for a faculty member j (CI_j) thus became

$$CI_j = \sum_{r \in R} w_r I_{rj}^n, \ 0 \le w_r \le 1, \tag{2}$$

where w_r is the weight of an indicator r, and $\sum_{r \in R} w_r = 1$. The linear aggregation principle used in the construction of CI in (2) permitted us to estimate the marginal contribution of each indicator as measured by its relative importance (i.e., weight) in the CI separately. Given the weights, the higher the score of a particular indicator, the higher is its contribution to the CI score. Given the indicators, the higher the weight of an indicator, the higher is its contribution to the CI value. Therefore, the higher the CI value, the more productive is the faculty member, and vice versa. Note that this linear aggregation rule holds under the condition that the individual indicators are independent (i.e., the preference relation between indicators is non-compensatory).

In making an aggregation as nice and meaningful index, we considered two issues. First, should the weights be determined in a subjective or objective manner? Second, should preference relation for different indicators be guided by compensatory or non-compensatory principles? We opted for the objective weights to avoid arbitrariness associated with the subjective opinion-based methods. The linear aggregation principle employed in (2) implicitly assumed a constant trade-off between different indicators. This assumption is questionable if the law of diminishing marginal rate of substitution (MRS)[10] applied to the indicators. Under such circumstance, the linearity assumption may produce biased estimates when non-linear trade-off is going on between the indicators [63,64]. In most practical applications where the compensatory relation was not appropriate, we needed a method that could accommodate the non-compensatory preference structure among individual indicators.

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[10] The law of diminishing MRS states that for an individual j, the relative importance of I_{1j} as compared to I_{2j}, increases when the value of I_{1j} decreases relative to I_{2j}.

The BOD model has been extensively applied to objectively generate weights of the individual indicators in the construction of CI in several areas.[11] The classical BOD [44], a special case of the CCR-DEA model by Charnes et al. [66] without any input, can be one way of constructing the BOD estimator of CI of a faculty member o (CI_o^{BOD}) as measured by output efficiency parameter θ.[12] Here, CI_o^{BOD} lies between 0 (worst performance) and 1 (best performance). Symbolically, $0 < \text{CI}_o^{BOD} \leq 1$. We noted three problems in using this classical BOD-based CI measure. First, the weights generated on six individual indicators were faculty-member specific that made area-wise comparisons rather hard. Second, weights were not uniquely determined (i.e., multiple weights were generated) when there were no constraints on weights. Finally, the BOD model sometimes generated unacceptable zero weights.

The solutions proposed in the literature for dealing with the foregoing problems of multiple and/or zero weights (see, e.g., Fusco [65] on the detailed references on these) include value judgments by either imposing bounds on the weights or setting *a priori* weights. Since such value judgments vary across analysts/experts, the weights suffer from obvious arbitrariness. Therefore, we adjudged the ratings based on the arbitrary weight restrictions principle as unacceptable. Moreover, as Podinovski [67] also pointed out, the BOD model imposes the compensatory preference relation among individual indicators without actually verifying whether this relation actually exists in the data.

We saw merit in following the advice of Fusco [65] who recommended including directional penalties in the BOD model. More specifically, the directional distance function (DDF) of Chamber et al. [68] accommodates the non-compensatory preference relations among indicators rather well. To compute the directional BOD (*D-BOD*) estimator of the CI of research productivity for a faculty member o ($o \in J$), therefore, we set up the following linear program under the variable returns to scale (VRS) specification of Banker et al. [69] as

$$\left(\text{CI}_o^{D-BOD}\right)^{-1} - 1 = \max_{\beta, \lambda} \sum_{r \in R} \left(g_r / G\right) \beta_r \tag{3}$$

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[11] These include capital construction program choice, economic welfare, social inclusion policies, quality of higher education, human development index, internal market policies, local police effectiveness, macroeconomic performance, monetary aggregation, R&D programs evaluation, sustainable energy development, sports, technology achievement index, etc. See the Sahoo and Acharya [42] and Fusco [65] for the detailed references on these application areas.

[12] $\text{CI}_o^{BOD} = \max_{\theta, \lambda} \theta$ subject to $\sum_{j \in J} I_{rj}^n \lambda_j \geq I_{ro}^n \theta$ (for all $r \in R$), $\lambda_j \geq 0$ (for all $j \in J$).

$$\text{subject to} \quad \sum_{j \in J} I_{rj}^n \lambda_j \geq I_{ro}^n + \theta_r g_r, \ r \in R, \tag{3.1}$$

$$\sum_{j \in J} \lambda_j = 1, \tag{3.2}$$

$$\lambda_j \geq 0 \qquad \text{for all } j \in J, \tag{3.3}$$

where $G = \sum_{r \in R} g_r$. Here g_r's are the endogenous directional indicators representing as directional penalties,[13] and β_r represents the rate of maximum improvement in the rth indicator of faculty member o. Thus, the higher the value of β, the more inefficient is the faculty member, and vice versa. If $\beta_r = 0$ for all $r \in R$, then the faculty member o $(o \in J)$ is most productive, in which case $\text{CI}_o^{D-BOD} = 1$. Technically, $0 < \text{CI}_o^{D-BOD} \leq 1$.

The technology structure employed in the *D-BOD* model (3) uses λ as weights to form a linear combinations of *N* observed faculty members. Here the variable λ (or correspondingly, the dual multiplier w of the constraint (3.1) of model (3)) can be interpreted as *intensities* (or *importance*) *coefficients* depending on whether the preference relation among indicators is compensatory (or non-compensatory). The assumption of VRS is maintained by the restriction (3.2) that the sum of these λ variables is 1. The indicators are assumed to be strongly disposable, and this assumption is secured by the use of inequality ($\geq$) constraints in (3.1).

The objective function of our model (3) aimed at measuring CI_o^{D-BOD} by looking at the maximum possible improvements in each and every individual indicator represented by β_r $(r \in R)$. Each improvement parameter β_r carried a weight in term of its relative importance, i.e., (g_r/G). The weighted sum, i.e., $\sum_{r \in R} (g_r/G) \beta_r$ could then be interpreted as the maximum overall percentage improvement along all the six indicators. The *D-BOD* estimator CI in terms of output efficiency was then computed as $1 / \left(1 + \sum_{r \in R} (g_r/G) \beta_r\right)$. Our CI construct is both theoretically and empirically appealing: It first involves differential expansions in individual indicators due to their differing opportunity costs and thus satisfies one important 'indication' property of an ideal efficiency measure and then entails aggregation of improvements in indicators with unequal weights depending upon their relative importance.

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[13] Note that most of the earlier studies employing directional distance function had considered the uses of several exogenous direction vectors. See, e.g., Sahoo et al. [70] and Mehdiloozad et al. [71] for the details.

The directional penalty vector g used in (3) revealed the endogenous preference structure among indicators. Using the principal component analysis (PCA), this preference structure was determined from the principle of variability of each indicator (as measured by robust kernel variance) projected on to principal components (PCs). This principle implied that an indicator with a high variability was more important than the indicator with low variability in discriminating decision making units. The PCA allowed us to create an order of PCs in which the first PC had the highest kernel variance and each succeeding component had the highest variance possible under the condition that it be orthogonal to the preceding components. Following this, we calculated the direction vector g as

$$g = \left(g_1, g_2, \ldots, g_6\right) = \left(I_{pc1}, I_{pc2} \cdot \frac{\text{var}(\hat{I}_{pc2})}{\text{var}(\hat{I}_{pc1})}, \ldots, I_{pc6} \cdot \frac{\text{var}(\hat{I}_{pc6})}{\text{var}(\hat{I}_{pc1})}\right). \tag{4}$$

In Equation (4), I_{pc1} is the original individual indicator that is most correlated with the first PC; I_{pc2} is the original individual indicator most correlated with the second PC2 and so on; and $\text{var}(\hat{I}_{pc1})$ represents the kernel variance of the projected value of I_1 onto the PC, $\hat{I}_{pc1}$; $\text{var}(\hat{I}_{pc2})$ represents the kernel variance of the projected value of I_2 onto the principal component, $\hat{I}_{pc2}$; and so on. While the slope of the first PC (i.e., I_{pc1}) represents the direction g, the ratio of any two kernel variances of indicators projected onto the PCs (i.e., $\text{var}(\hat{I}_{pc2})\big/\text{var}(\hat{I}_{pc1})$) represents the intensity of the rates of substitution between I_1 and I_2.

Note that the *D-BOD* model presented in (3) is more general, and is different from the one suggested by Fusco [65] in two key ways. First, unlike in Fusco [65], the rates of improvements in individual indicators represented by β s are different due to their differing opportunity costs, and the resulting efficiency involves the aggregation of improvements in indicators with unequal weights depending on their relative importance. Our measure of CI was well behaved under less restrictive assumptions, and hence is theoretically more appealing than that of Fusco [65]. Second, the VRS specification represented by $\sum_{j=1}^{784} \lambda_j = 1$ was always maintained. Essentially, then, the *D-BOD* model of Fusco [65] was a special case of our D-BOD model (3) when $\beta_r = \beta$ for all r, the VRS-specification constraint (3.2) was removed.

Given the objectivity in the *D-BOD* model (3), we saw three more merits in our analyses. First, we determined weights endogenously. Second, we included the directional distance function to avoid the use of arbitrary weight restrictions/bounds by the policy analysts. Finally, the D-BOD estimator of efficiency satisfied one important 'indication' property (i.e., an ideal efficiency measure be an aggregation of differential improvements in indicators with unequal weights depending upon their relative importance.)

4. Results

Of the 1,416 faculty members in the 32 B-Schools of India, only 784 (i.e., 55.37%) had at least one publication captured in one of the three databases (i.e., NUS, ABS, or *Scopu*s). Across 32 B-schools, 56.40% of the faculty members had published at least one journal article. While 92.31% management faculty members of the IIT, Madras were research active, only 16.28% of those at the S P Jain Management School, Mumbai were so.

We present the distribution of 5,551 papers by those faculty members over 1968 to 2014 in Fig.1. As it can be seen, the publications of the chosen years suggest three developmental stages or career priorities among them. Those of 1968-86 were research inactive; those of 1987-97 started putting priority on research and publications; and those of 1998-2014 accepted research as one of their career priorities. Apparently, then, the B-Schools in India have been steadily progressing in putting research as one of their key focus areas.
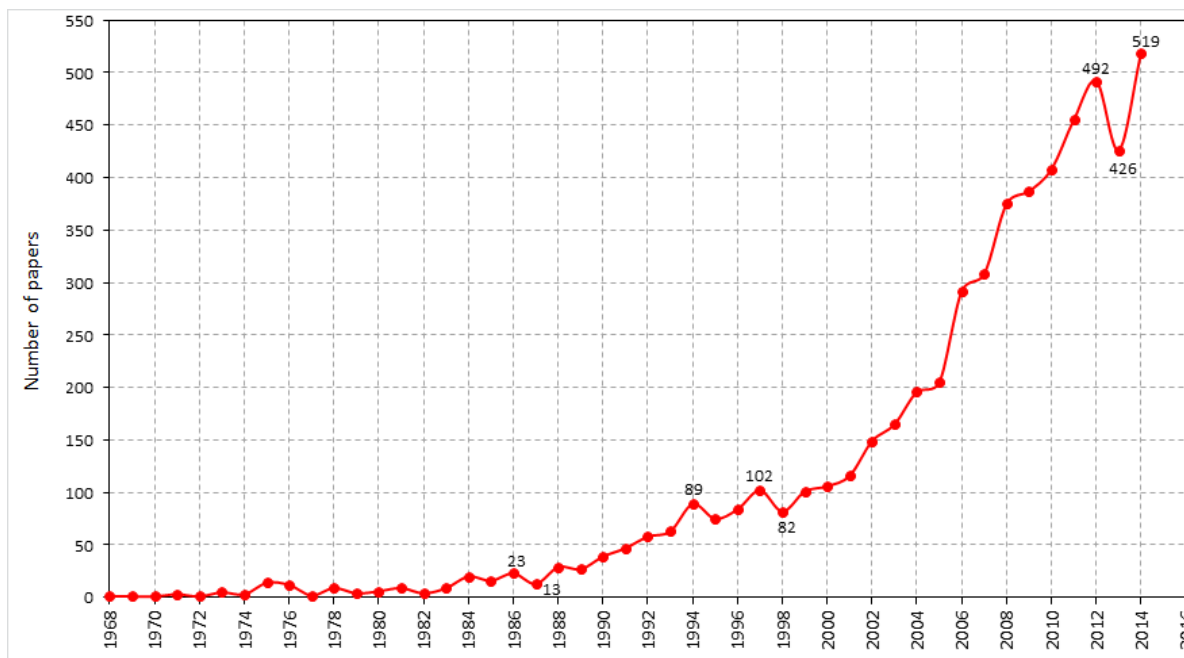
Fig. 1. Distribution of published papers over years.

4.1 Descriptive statistics

To examine research productivity at the organizational level, we first considered all of our six indicators along with the number of research years spent by the faculty members in the public and private B-Schools. Recall that IITs, IIMs, and CUs are run by the GOI but other schools by private individuals and/or groups. Further, while IIMs are exclusively B-Schools, IITs and CUs have a faculty or school of management. In Table 1, we present the means (Ms), Standard Deviations (SDs), and range of research productivity as revealed by each of the six indicators.

Table 1. Ms, SDs, and range of research productivity indicators at different groups of B-Schools

		Research experience (in years)	Author h-index	Total Citations	No. of papers	Tier score	Journal h-index	IF
I	**All ($N = N_1 + N_2 = 784$)**							
	M	14.142	4.282	172.897	7.079	24.562	121.291	4.285
	SD	9.403	4.263	454.285	10.753	48.348	230.521	7.373
	Minimum	1	0	0	1	0	0	0
	Maximum	52	48	7115	167	661.714	3056.665	83.031
I.1	**Public ($N_1 = N_3 + N_4 = 550$)**							
	M	14.076	4.529	197.036	7.736	26.556	135.743	4.698
	SD	9.093	4.615	518.770	11.981	46.758	246.920	7.694
	Minimum	1	0	0	1	0	0	0
	Maximum	42	48	7115	167	528.568	3056.665	83.031
I.1.a	**IIMs ($N_3 = 392$)**							
	M	13.620	4.135	166.760	6.671	26.927	130.394	4.374
	SD	9.185	3.786	312.641	7.621	41.600	212.015	6.462
	Minimum	1	0	0	1	0	0	0
	Maximum	42	21	2034	70	328.572	2275.075	61.790
I.1.b	**Non-IIMs ($N_4 = 158$)**							
	M	15.209	5.506	272.152	10.380	25.635	149.015	5.501
	SD	8.787	6.116	830.467	18.639	57.741	317.812	10.104
	Minimum	1	0	0	1	0	0	0
	Maximum	40	48	7115	167	528.568	3056.665	83.031
I.2	**Private ($N_2 = 234$)**							
	M	14.295	3.701	116.158	5.534	19.876	87.324	3.316
	SD	10.112	3.225	234.104	6.852	51.695	182.395	6.471
	Minimum	1	0	0	1	0	0	0
	Maximum	52	19	1820	51	661.714	1915.143	52.645

As Table 1 shows, the public B-schools outperformed the private ones along all six indicators. In fact, comparisons between means of these groups yielded statistically significant one-tailed t ratios, ts (782)

≥ 1.703, ps ≤ 0.05. Among the public B-schools, however, the non-IIM schools outperformed the IIMs only on two indicators - author h-index and number of paper, ts (548) ≥ 2.421, ps < 0.01; but not on the other four indicators, ts(548) ≤ 1.551, ps ≥ .06.

4.2 Top productive schools and researchers

We examined the CI of research productivity of an individual faculty member in three ways. In the first, we estimated the overall CI of research productivity over the entire period of 1968-2014 (Scheme I, N = 784). Although this analysis estimated one's overall contributions, it did ignore the number of years one had spent over research. In the second, therefore, we corrected the CI scores of individual faculty members by the number of years they had spent on research after their respective doctoral degree during the same period of 1968-2014 (Scheme II, N = 784). That is, we calculated CI for each year and then averaged the yearly-CI to get one CI score. In the final, we estimated the CI in the same way as in Scheme I but for only the most recent ten years of 2004 to 2014 (Scheme III, N = 738). Thus, the CI from Schemes I, II, and III estimated the total productivity over one's career, the average productivity over the number of years one had spent over research, and the total productivity during recent years. We did the third analysis because Fig. 1 suggested that research might have become a career priority of faculty members in recent years [72].

Before executing the *D-BOD* model (3), we considered the directional penalties (i.e., the direction vector). As we noted, there were three sets of data, one based on the normalized individual indicators at the aggregate level for 1968-2014; another based on the normalized year-based indicators for the same period; and still another based on the normalized individual indicators at the aggregate level for 2004-2014. To determine the relative importance of the six indicators as measured by their respective variances, we first did principal component analysis (PCA) of the foregoing three data sets. Results from the first two sets of data converged in identifying the relative importance of six indicators wherein the journal tier was the most important indicator with a maximum variance of 29.403 (28.515), followed by the total citations with a maximum variance of 22.619 (18.297), the journal IF with a maximum variance of 17.664 (18.031), the author h-index with a maximum of variance 15.772 (17.895), the number of papers with a maximum variance of 13.661 (15.652), and the journal h-index with a maximum variance 0.882 (1.611). The number in brackets represents the variances obtained from the second set of data. In the third set of data, however, there were changes only in the order of third and fourth PCs. The journal tier became the most important indicator with a maximum variance of 31.652, followed by the total citations with a maximum variance of 24.506, the author h-index with a maximum variance of 16.678, the IF with a maximum variance of 15.437,

16

the number of papers with a maximum variance of 10.150, and the journal *h*-index with a maximum variance of 1.577, respectively. We used these variances in estimating the directional penalties for each of the 784 researchers for the first two sets of the data, and for the 738 researchers in the third set of the data, using formulae (4). Our *D-BOD* modeling (3) used these directional penalties in computing the CI of research productivity. It deserves emphasis that the shift in relative importance of the author's *h*-index from the fourth position in Schemes I and II to the third position in Scheme III does point to a greater involvement of individual faculty members in research in the most recent than the total years of 1968-2014 examined.

4.2.1 Top productive schools

In Table 2, we list the mean CI of faculty members from B-Schools during 1968-2014 (i.e., Scheme I).[14] We have put on * the business school *M*s that were significantly greater than zero. In Table 3, we report the same results by ownerships of the schools.

Table 2. B-Schools listed according to their mean CIs from high to low.

Rank	Schools	*M*	*SD*	*Minimum*	*Maximum*	*n*
1	IIT Delhi	0.1054*	0.250	0.005	1	15
2	Great Lakes	0.0957	0.285	0.002	1	12
3	IIT Madras	0.0862**	0.204	0.005	1	24
4	IISc	0.0640***	0.061	0.011	0.201	10
5	IIT Bombay	0.0587***	0.058	0.003	0.204	16
6	ISB Hyderabad	0.0461***	0.032	0.008	0.133	31
7	IIM Bangalore	0.0428***	0.054	0.002	0.358	80
8	IIM Ahmedabad	0.0384***	0.035	0.002	0.185	79
9	MDI Gurgaon	0.0368***	0.050	0.003	0.177	31
10	IIM Calcutta	0.0332***	0.046	0.003	0.298	63
11	IIT Kanpur	0.0306***	0.032	0.003	0.122	17
12	IIM Kashipur	0.0248***	0.019	0.003	0.053	13
13	IIM Rohtak	0.0248***	0.027	0.003	0.077	12
14	IIM Lucknow	0.0220***	0.021	0.003	0.098	27
15	IIM Raipur	0.0216**	0.039	0.002	0.122	16
16	IIT Kharagpur	0.0211***	0.017	0.002	0.056	12
17	XIM Bhubaneswar	0.0187***	0.025	0.002	0.121	22
18	IIM Kozhikode	0.0170***	0.018	0.002	0.089	35
19	MICA	0.0166***	0.015	0.002	0.050	11
20	FMS Delhi	0.0163**	0.012	0.009	0.038	6
21	IMT Gaziabad	0.0163***	0.018	0.002	0.087	31

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[14] Similar rankings of schools based on the second and third ranking schemes are not reported here due to lack of space, but are available upon request from the authors.

22	XLRI Jamshedpur	0.0158[***]	0.015	0.003	0.062	26
23	IIFT Delhi	0.0148[***]	0.014	0.002	0.056	20
24	IIM Trichy	0.0148[***]	0.012	0.003	0.048	14
25	IMI Delhi	0.0143[***]	0.015	0.002	0.049	38
26	NITIE	0.0140[***]	0.010	0.002	0.042	38
27	IIM Udaipur	0.0133[**]	0.019	0.002	0.066	10
28	IIM Ranchi	0.0129[***]	0.009	0.002	0.027	8
29	IIM Indore	0.0114[***]	0.014	0.002	0.069	35
30	NMIMS	0.0107[***]	0.009	0.002	0.031	12
31	TAPMI	0.0067[***]	0.007	0.002	0.030	13
32	SP Jain Mumbai	0.0051[***]	0.003	0.002	0.011	7

Note: [*] $p < 0.10$; [**] $p < 0.05$; and [***] $p < 0.01$.

Table 3. Ms, SDs, and range of CI of the different groups of schools from Scheme I

			Minimum	Maximum	M	SD	Ns
All			0.0016	1	0.0313[***]	0.0702	784
	Public		0.0016	1	0.0336[***]	0.0703	550
		IIMs	0.0016	0.3576	0.0295[***]	0.0384	392
		Non-IIMs	0.0021	1	0.0438[***]	0.1161	158
		IITs	0.0023	1	0.0638[***]	0.1545	84
		Non-IITs	0.0021	0.2009	0.0212[***]	0.0294	74
	Private		0.0016	1	0.0257[***]	0.0699	234

[***] $p < 0.01$

Taken together, results reported in Tables 2 and 3 lead to three observations. First, the Ms of 31 of the 32 B-Schools are significantly greater than zero.[14] Second, productivity at public and private B-Schools is the same (t (782) = 1.442, $p = 0.15$), as is the productivity at IIMs and non-IIMs (t (548) =1.524, $p = 0.129$). Finally, B-Schools of IITs outperformed those of the non-IITs (t (156) = 2.481, $p = 0.015$) and even IIMs (t (474) = 2.025, $p = 0.046$). Among the B-Schools of India, therefore, those at the IITs may be adjudged as the best performing ones at the moment.[15]

Given the foregoing evidence for a seemingly better productivity at B-Schools of the IITs than those of the non-IITs, we examined the difference between faculty members who had their doctoral training (i) in India *versus* abroad, (ii) at IIMs *versus* non-IIMs, and (iii) at IIMs *versus* IITs. We present the

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[15] The top three Ms of Table 2 were essentially due to one superstar in each business school. When we removed such an outlier, the Ms of CI of research productivity of IIT Delhi, Great Lakes, and IIT Madras came down to 0.042, 0.014, and 0.047 with respective SDs of 0.0372, 0.0128, and 0.0620. These new Ms were significantly greater than zero at $p < 0.01$.

results in Table 4. Those trained at non-IIMs were no different from their IIM counterparts, t (583) =1.605 p = 0.109. Likewise, those trained at IITs, compared to IIMs, were more productive t (257) = 1.656, p = 0.049. Interestingly, the productivity of those trained abroad was nearly two times as large as that of those trained in India, t (782) = 1.650 , p = 0.049. The quality of doctoral training in B-Schools of India seems to be a more likely debilitating factor behind the less number of publications in international journals [13] than factors suggested [12].

Table 4. Training differences in research productivity

Doctoral trainings from	N	M	SD	t
Non-IIMs	128	0.027	0.0719	1.605
IIMs	457	0.021	0.0250	
IITs	128	0.043	0.1258	1.656[**]
IIMs	131	0.021	0.0250	
Abroad	199	0.047	0.0828	1.650[***]
India	585	0.026	0.0647	

Note: [**] p < 0.05; and [***] p < 0.01.

4.2.1 Top 5% productive researchers from the three schemes

We made distributions of the CI estimated from Schemes I, II, and III, and identified those who fell in the top 5% of each distribution. We list the names and their respective research productivity of those faculty members from Schemes I, II, and III in Tables 5, 6, and 7, respectively. As anticipated, all the three tables are instructive for different reasons. While the indicators over the total years indicate the long-term dedication to and persistence in research of a faculty member, those at the year-wise level suggest the priority for research regardless of one's career in academia.[16] Thus, relatively younger researchers, for example, Rajesh Pillania, Pulak Ghosh, and Sumeet Gupta, to mention a few, who did not fare so well on all indicators in Scheme I (i.e., their respective ranks are 12, 17, and 35 in Table 5) easily made to top of the list according to Scheme II (i.e., their respective ranks are 2, 5, and 7 in Table 6). Notably, the CIs from Schemes I and II point to the long- and short-term priorities for research in one's career, respectively. Finally, Table 7 presents mean productivity from Scheme III. In addition to the priority for research in their careers, these estimates reflect on the relevance of these 5% scholars in generating contemporary management literature.

Table 5. Top 5% of most productive researchers from Scheme I (1968-2014)

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[16] A difficulty with this interpretation would arise when a young researcher within three to four years of completing the PhD published a few papers in Tier 1 journals could score very high on high indicators such as tier, *h*-index, and IF and thus remain within the top 5% productive researches. To eliminate such bias, we set the minimum number of the post-PhD years of research experience to 5.

Rank	Researcher	Current Affiliation	PhD	Area of research	Research exp. in years	Author *h*-index	Citations	No. of papers	Tier score	Journal *h*-index	IF	CI
1	C Rajendran	IIT Madras	IIT Madras	OM	25	48	7115	129	528.57	3056.66	83.03	1
1	Bala V Balachandran	Great Lakes	Carnegie Mellon	A&F	52	17	1325	51	661.71	1915.14	52.64	1
1	Ravi Shankar	IIT Delhi	IIT Delhi	OM	16	43	6864	167	218.35	1292.26	57.18	1
4	Ramadhar Singh	IIM Bangalore	Purdue	OB&HRM	42	18	1048	70	328.57	2275.07	61.79	0.358
5	Indranil Bose	IIM Calcutta	Purdue	MIS	19	21	1242	46	254.05	1761.77	55.71	0.298
6	T T Narendran	IIT Madras	IIT Madras	OM	39	21	2112	63	188.45	948.18	27.44	0.242
7	VK Kathuria	IIT Bombay	IGIDR	Econ.	17	17	1160	40	206.02	971.77	31.71	0.204
8	P Balachandra	IISc	IISc Bangalore	SM	25	17	1067	36	167.04	869.18	41.07	0.201
9	Debashis Saha	IIM Calcutta	IIT Kharagpur	MIS	24	18	2034	35	108.53	707.32	31.97	0.190
10	Amit Garg	IIM Ahmedabad	IIM Ahmedabad	SM	17	16	1085	35	130.49	1297.94	36.47	0.185
11	Sajal Ghosh	MDI Gurgaon	N.A.	Econ.	14	11	777	25	183.93	888.90	41.82	0.177
12	RK Pillania	MDI Gurgaon	N.A.	SM	10	13	449	50	89.29	658.80	51.95	0.176
13	RP Sundarraj	IIT Madras	Tennessee	MIS	28	14	781	31	171.38	1009.32	32.34	0.171
14	Vijay Aggarwal	MDI Gurgaon	Case Western Reserve	OM	36	19	1110	22	180.24	803.12	20.77	0.167
15	Gajendra K Adil	IIT Bombay	Manitoba	OM	27	12	525	37	185.36	859.14	26.90	0.158
16	D Tirupati	IIM Bangalore	MIT	OM	31	16	1225	32	142.79	573.89	17.78	0.149
17	Pulak Ghosh	IIM Bangalore	Oakland	DS	12	19	516	24	170.07	864.30	17.26	0.146
18	S G Badrinath	IIM Bangalore	Purdue	A&F	31	11	1578	17	155.95	619.24	20.63	0.144
19	TT Ram Mohan	IIM Ahmedabad	Stern	A&F	35	8	249	31	302.38	483.81	10.46	0.142
20	PR Shukla	IIM Ahmedabad	Stanford	SM	29	17	855	33	86.43	678.68	25.46	0.141
21	M H Bala Subrahmanya	IISc	ISEC Bangalore	Econ.	22	13	640	35	141.90	609.24	23.38	0.140
22	B Mahadevan	IIM Bangalore	IIT Madras	OM	25	12	1559	21	126.71	740.72	18.82	0.138
23	Jayant R Kale	IIM Bangalore	Univ. of Texas at Austin	A&F	28	12	1296	12	153.62	630.93	21.80	0.138
24	D Banwet	IIT Delhi	IIT Delhi	OM	23	19	1649	48	31.95	268.73	15.24	0.136
25	Sanjay Kallapur	ISB Hyderabad	Harvard	A&F	25	12	1820	12	137.86	412.57	15.62	0.133
26	A Patwardhan	IIT Bombay	Carnegie Mellon	MIS	32	18	1560	27	50.63	464.02	19.30	0.132
27	G Srinivasan	IIT Madras	IIT Madras	OM	25	12	912	28	119.83	648.75	21.23	0.129
28	LS Ganesh	IIT Madras	IIT Madras	OM	29	16	1328	26	78.61	495.33	16.06	0.125
29	M Patibandla	IIM Bangalore	JNU	SM	27	10	535	24	198.21	608.14	13.09	0.124
30	Kripa Shanker	IIT Kanpur	Cornell	OM	40	11	804	23	149.68	634.94	16.34	0.122
31	BS Sahay	IIM Raipur	IIT Delhi	OM	20	19	1334	26	39.48	338.74	17.69	0.122
32	Biresh K Sahoo	XIM Bhubaneswar	IIT Kharagpur	Econ.	16	13	530	24	124.43	866.46	19.53	0.121
33	U Dinesh Kumar	IIM Bangalore	IIT Bombay	DS	21	14	816	26	96.71	648.49	19.59	0.121
34	Pankaj Chandra	IIM Bangalore	Wharton	OM	26	13	1123	15	126.67	597.80	12.72	0.116
35	Sumeet Gupta	IIM Raipur	NUS	MIS	9	16	1405	25	65.34	357.83	12.59	0.116
36	Sukhpal Singh	IIM Ahmedabad	ISEC Bangalore	SM	25	13	772	26	136.83	373.92	9.95	0.112
37	R Chakrabarti	ISB Hyderabad	UCLA	A&F	16	14	980	16	107.37	433.42	14.04	0.111
38	A Shaw	IIM Calcutta	Univ. of Illinois at Urbana-Champaign	SM	31	9	244	18	183.33	387.67	15.02	0.108

| | 39 | Ishwar Murthy | IIM Bangalore | Texas A&M | DS | 28 | 8 | 417 | 22 | 138.05 | 742.49 | 17.80 | 0.106 |
| | 40 | Dishan Kamdar | ISB Hyderabad | NUS | OB&HRM | 11 | 11 | 950 | 14 | 80.95 | 588.86 | 18.22 | 0.102 |

Table 6. Top 5% productive researchers from Scheme II (1968-2014)

Rank	Researcher	Affiliation	PhD	Area	Reseach exp. (years)	Author h-index	Total citations	No. of papers	Tier score	Journal h-index	IF	CI
1	C Rajendran	IIT Madras	IIT Madras	OM	25	48	7115	129	528.57	3056.66	83.03	1
1	Ravi Shankar	IIT Delhi	IIT Delhi	OM	16	43	6864	167	218.35	1292.26	57.18	1
1	RK Pillania	MDI Gurgaon	N.A.	SM	10	13	449	50	89.29	658.80	51.95	1
4	Indranil Bose	IIM Calcutta	Purdue	MIS	19	21	1242	46	254.05	1761.77	55.71	0.418
5	Pulak Ghosh	IIM Bangalore	Oakland	DS	12	19	516	24	170.07	864.30	17.26	0.358
6	Sajal Ghosh	MDI Gurgaon	N.A.	Econ.	14	11	777	25	183.93	888.90	41.82	0.338
7	Sumeet Gupta	IIM Raipur	NUS	MIS	9	16	1405	25	65.34	357.83	12.59	0.324
8	VK Kathuria	IIT Bombay	IGIDR	Econ.	17	17	1160	40	206.02	971.77	31.71	0.312
9	SM Kunnumkal	ISB Hyderabad	Cornell	DS	9	8	212	15	120.71	510.24	14.96	0.282
10	Amit Garg	IIM Ahmedabad	IIM Ahmedabad	SM	17	16	1085	35	130.49	1297.94	36.47	0.272
11	P R Srivastava	IIM Rohtak	BITS Pilani	MIS	7	12	498	22	10.16	204.00	18.76	0.260
12	Mukta Kulkarni	IIM Bangalore	Univ. of Texas at San Antonio	OB&HRM	9	6	560	20	88.17	375.78	16.19	0.248
13	Dishan Kamdar	ISB Hyderabad	NUS	OB&HRM	11	11	950	14	80.95	588.86	18.22	0.239
14	K Mukherjee	IIM Bangalore	INSEAD	OB&HRM	6	3	57	5	59.71	354.56	15.20	0.231
15	Deepa Mani	ISB Hyderabad	Univ. of Texas	MIS	9	7	331	6	99.90	305.09	15.66	0.230
16	Sarang Deo	ISB Hyderabad	UCLA	OM	10	7	207	12	106.79	547.44	13.44	0.220
17	Amit Mehra	ISB Hyderabad	Rochester	MIS	9	5	114	7	103.45	320.74	17.32	0.220
18	R Chittoor	ISB Hyderabad	IIM Calcutta	SM	8	5	442	8	71.31	302.46	12.39	0.205
19	Biresh K Sahoo	XIM Bhubaneswar	IIT Kharagpur	Econ.	16	13	530	24	124.43	866.46	19.53	0.200
20	Bala V Balachandran	Great Lakes	Carnegie-Mellon	A&F	52	17	1325	51	661.71	1915.14	52.64	0.200
21	S K Srivastava	IIM Lucknow	IIM Lucknow	OM	11	8	1798	11	45.24	296.24	17.71	0.198
22	Smeeta Mishra	IMT Ghaziabad	Univ. of Texas at Austin	OB&HRM	9	6	99	11	110.71	177.29	4.70	0.191
23	Ramendra Singh	IIM Calcutta	IIM Ahmedabad	Marketing	7	7	156	21	36.37	223.53	8.46	0.190
24	TT Niranjan	IIT Bombay	MDI Gurgaon	OM	8	8	138	15	53.19	270.29	9.78	0.189
25	P Balachandra	IISc	IISc Bangalore	SM	25	17	1067	36	167.04	869.18	41.07	0.188
26	Ramadhar Singh	IIM Bangalore	Purdue	OB&HRM	42	18	1048	70	328.57	2275.07	61.79	0.185
27	I Mukherjee	IIT Bombay	IIT Kharagpur	OM	9	7	412	15	44.67	358.23	14.40	0.180
28	R Chakrabarti	ISB Hyderabad	UCLA	A&F	16	14	980	16	107.37	433.42	14.04	0.174
29	Debashis Saha	IIM Calcutta	IIT Kharagpur	MIS	24	18	2034	35	108.53	707.32	31.97	0.173
30	A Nandkumar	ISB Hyderabad	Carnegie Mellon	SM	9	7	199	4	83.33	275.67	6.89	0.172
31	Abhijeet Vadera	ISB Hyderabad	Univ. of Illinois	OB&HRM	7	5	211	5	49.81	212.09	9.91	0.171
32	Rohit Varman	IIM Calcutta	Univ. of Utah	Marketing	13	10	451	18	98.67	228.66	11.04	0.168

33	Gopal Das	IIM Rohtak	IIT Kharagpur	Marketing	6	5	63	13	20.60	218.95	10.77	0.165
34	J Bhatnagar	MDI Gurgaon	IIT Delhi	OB&HRM	12	15	962	19	34.81	298.64	7.97	0.163
35	Surya P Singh	IIT Delhi	IIT Kanpur	DS	13	9	376	16	90.14	427.61	12.36	0.162
36	MH Bala Subrahmanya	IISc	ISEC Bangalore	Econ.	22	13	640	35	141.90	609.24	23.38	0.157
37	R P Sundarraj	IIT Madras	Tennessee	MIS	28	14	781	31	171.38	1009.32	32.34	0.147
38	Gajendra K Adil	IIT Bombay	Manitoba	OM	27	12	525	37	185.36	859.14	26.90	0.146
39	Haritha Saranga	IIM Bangalore	Univ. of Exeter	OM	18	11	450	18	108.02	655.51	16.16	0.142
40	Prachi Deuskar	ISB Hyderabad	New York Univ.	A&F	8	6	125	4	55.24	169.26	6.36	0.142

Table 7. Top 5% productive researchers from Scheme III (2004-2014)

Rank	Author	Affiliation	PhD	Area	Author h-index	Total citations	No. of paper	Tier score	Journal h-index	IF	CI
1	Indranil Bose	IIM Calcutta	Purdue	MIS	19	910	39	215.95	1453.82	45.50	1
1	Ravi Shankar	IIT Delhi	IIT Delhi	OM	41	6328	159	203.81	1248.31	55.37	1
3	C Rajendran	IIT Madras	IIT Madras	OM	26	1986	60	119.01	807.05	27.98	0.347
4	Sajal Ghosh	MDI Gurgaon	N.A.	Econ.	9	439	23	157.26	766.90	38.13	0.276
5	RK Pillania	MDI Gurgaon	N.A.	SM	13	449	50	89.29	658.80	51.95	0.269
6	Pulak Ghosh	IIM Bangalore	Oakland	DS	10	323	24	170.07	864.30	17.26	0.244
7	P Balachandra	IISc	IISc	SM	14	868	23	112.68	633.12	30.00	0.236
8	Amit Garg	IIM Ahmedabad	IIM Ahmedabad	SM	12	528	25	103.11	851.55	25.33	0.210
9	Biresh K Sahoo	XIM Bhubaneswar	IIT Kharagpur	Econ.	13	431	21	118.24	807.65	16.90	0.203
10	TT Ram Mohan	IIM Ahmedabad	Stern	A&F	7	126	19	182.38	291.81	6.31	0.195
11	MH Bala Subrahmanya	IISc	ISEC Bangalore	Econ.	13	562	28	94.76	526.38	21.69	0.189
12	VK Kathuria	IIT Bombay	IGIDR	Econ.	14	449	25	96.86	573.10	18.43	0.184
13	PR Shukla	IIM Ahmedabad	Stanford	SM	13	621	27	77.59	618.88	23.73	0.181
14	SM Kunnumkal	ISB Hyderabad	Cornell	DS	8	212	15	120.71	510.24	14.96	0.167
15	Dishan Kamdar	ISB Hyderabad	NUS	OB&HRM	11	950	14	80.95	588.86	18.22	0.167
16	Sumeet Gupta	IIM Raipur	NUS	MIS	16	1405	25	65.34	357.83	12.59	0.167
17	D Banwet	IIT Delhi	IIT Delhi	OM	18	1513	43	27.07	265.69	14.67	0.152
18	Sarang Deo	ISB Hyderabad	UCLA	OM	7	207	12	106.79	547.44	13.44	0.148
19	Haritha Saranga	IIM Bangalore	Univ. of Exeter	OM	9	335	14	96.36	533.85	11.90	0.145
20	Gajendra K Adil	IIT Bombay	Univ. of Manitoba	OM	8	355	24	90.12	420.33	13.43	0.143
21	Mukta Kulkarni	IIM Bangalore	Univ. of Texas at San Antonio	OB&HRM	6	560	20	88.17	375.78	16.19	0.143
22	Deepa Mani	ISB Hyderabad	Univ. of Texas	MIS	7	331	6	99.90	305.09	15.66	0.141

23	Amit Mehra	ISB Hyderabad	Rochester	MIS	5	114	7	103.45	320.74	17.32	0.137
24	Rohit Varman	IIM Calcutta	Univ. of Utah	Marketing	9	267	17	93.34	210.93	10.44	0.132
25	SK Srivastava	IIM Lucknow	IIM Lucknow	OM	6	1770	11	45.24	296.24	17.71	0.131
26	M Mathirajan	IISc	IISc	OM	13	520	19	55.24	372.89	12.93	0.125
27	T Bandyopadhyay	IIM Ahmedabad	Univ. of Calcutta	DS	6	111	19	89.19	460.62	11.21	0.125
28	RP Sundarraj	IIT Madras	Univ. of Tennessee	MIS	7	277	13	75.50	387.80	16.21	0.124
29	Surya P Singh	IIT Delhi	IIT Kanpur	DS	9	349	15	76.81	377.61	11.20	0.124
30	Smeeta Mishra	IMT Ghaziabad	Univ. of Texas at Austin	OB&HRM	6	99	11	110.71	177.29	4.70	0.121
31	A Patwardhan	IIT Bombay	Carnegie Mellon	MIS	16	1246	20	14.11	290.06	13.49	0.114
32	J Bhatnagar	MDI Gurgaon	IIT Delhi	OB&HRM	15	951	19	34.81	298.64	7.97	0.112
33	D'Cruz Premilla	IIM Ahmedabad	TISS	OB&HRM	10	263	16	64.21	196.97	10.31	0.109
34	Jayanthi Ranjan	IMT Ghaziabad	Jamia Millia Islamia	MIS	11	550	40	26.67	261.79	16.06	0.109
35	Sukhpal Singh	IIM Ahmedabad	ISEC Bangalore	SM	8	245	12	87.50	145.00	3.95	0.109
36	R Chittoor	ISB Hyderabad	IIM Calcutta	SM	5	442	8	71.31	302.46	12.39	0.108
37	A Nandkumar	ISB Hyderabad	Carnegie Mellon	SM	7	199	4	83.33	275.67	6.89	0.106
38	K Chaudhuri	IIM Bangalore	State Univ. of New York	Econ.	8	284	16	68.52	294.87	7.75	0.105
39	Arpita Khare	IIM Rohtak	Univ. of Allahabad	Marketing	9	206	37	35.62	274.02	16.85	0.103
40	Ramadhar Singh	IIM Bangalore	Purdue	OB&HRM	7	214	24	54.37	437.69	11.39	0.101

Note: A&F: Accounting and Finance, Econ.: Economics, OM: Operations Management, DS: Decision Sciences, MIS: Management Information Systems, OB&HRM: Organizational Behavior and Human Resource Management, and SM: Strategic Management, N. A.: Not Available

We present distributions of 40 star researchers from the three schemes across B-Schools in Table 8. Three suggestive trends can be noted.[17] First, 50% of the 32 B-Schools do have at least one star researcher according to one of the three schemes. Second, while 25% of star researchers are at the IIM Bangalore according to Scheme I and at the ISB Hyderabad according to Scheme II, such stars according to Scheme III are about equally distributed at the IIMs at Ahmedabad and at Bangalore and the ISB

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[17] For the sake of completeness, we examined the research productivity of faculty members who had earlier worked abroad and/or were on sabbatical leaves with that of those who worked only in India or had never been on sabbatical leave. Unfortunately, valid data were not available from the webpages of most faculty members. Through our personal contact, however, we came to know that some of the top 5% scores from Scheme I (e.g., Bala V Balachandran, Biresh K Sahoo, C Rajendran, Gajendra K Adil, Indranil Bose, P Balachandra, Ramadhar Singh, Sridhar Seshadri, etc. in Tables 5, 6, and 7) had in fact worked for some years or spent sabbatical leaves abroad. Importance of this information lies in suggesting that B-Schools in India might seriously consider sending the existing faculty members on sabbatical leaves to foreign B-Schools for self-renewal periodically.

Hyderabad. Finally, while the IIM Bangalore has been attracting impactful researchers from the very beginning, ISB Hyderabad can also be a good option for those skilled and interested in research.

Table 8. Schools' share of faculty members in top 5% list

Schools	Scheme I	Scheme II	Scheme III
Great Lakes	1	1	---
IIM Ahmedabad	4	1	6
IIM Bangalore	10	5	5
IIM Calcutta	3	4	2
IIM Lucknow	---	1	1
IIM Raipur	2	1	1
IIM Rohtak	---	2	1
IISc Bangalore	2	2	3
IIT Bombay	3	4	3
IIT Delhi	2	2	3
IIT Kanpur	1	---	---
IIT Madras	5	2	2
IMT Ghaziabad	---	1	2
ISB Hyderabad	3	10	7
MDI Gurgaon	3	3	3
XIM Bhubaneswar	1	1	1

In the most recent 10 years of 2004-2014 (Scheme III), there were 4,063 papers by 738 faculty members. Thus, we had earlier noted from Figure 1 that there has been a rise in publications in recent years. Further analyses of this period indicated that those who fell in the top 5% of CI distribution (i.e., Table 7) had contributed to 24.17% of these publications. We further divided the 738 faculty members into four quartiles as per their CI values in descending order. Those falling in Quartiles 1, 2, 3, and 4 from top to bottom had contributed to 57.05%, 23.23% 13.04%, and 6.67% of the total publications, respectively. Apparently, about 57% of the publications in even most recent years were by only the 25% of the current faculty members of B-Schools in India.

To determine the area-wise contributions, we report the number of star researchers from eight broad areas of management[18] according to Scheme I, II, and III in Table 9. There are four trends. First, as

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[18] Some areas such as Accounting (A) and Finance (F) are clubbed together since most of schools in India do not provide information separately in their webpages. So is the case with areas such as Organizational Behavior (OB) and Human Resource Management (HRM).

expected, those from the OM area have consistently been dominating in management research.[19] Second, some from economics, MIS, and strategy areas have also been consistent contributors. Third, there seem to improvements in short-term stars in OB & HRM. Finally, contributors from A&F, marketing, and DS still remain negligible.

Table 9. Area-wise share of faculty members in the top 5% list

Area	Scheme I	Scheme II	Scheme III
Accounting and Finance (A&F)	6	3	1
Operations Management (OM)	12	10	10
Decision Science (DS)	3	1	2
Economics	4	4	5
Marketing	0	3	2
Management Information System (MIS)	6	8	8
Organizational Behavior and Human Resource Management (OB&HRM)	2	7	6
Strategic Management (SM)	7	5	7

Note:

1) Three researchers (C Rajendran, Ravi Shankar, and Gajendra K Adil) are common across all the three schemes in OM area.
2) Five researchers (SM Kunnumkal, Sarang Deo, SK Srivastava, Surya P Singh, and Haritha Saranga) are common across Scheme II and Scheme III in OM area.
3) One researcher (Pulak Ghosh) is common across three schemes in DS area.

4.2.2 Top 10 productive researchers across disciplines

We examined the distribution of CIs from Scheme I and identified 10 top scores from seven areas of management. We report their scores on the six indicators and the overall CI in Table 10.[20] An examination of the names and their CIs reveals that 50% of these experts are at the three older IIMs at Ahmedabad, Bangalore, and Calcutta, and remaining 50% are scattered over remaining 13 schools. Among the private B-Scholars, however, the ISB Hyderabad stands out.

Table 10. Top 10 most productive researchers in different areas of management

Rank	Researcher	Affiliation	Ph.D	Research exp.	Author h-index	Total citations	No. of papers	Tier score	Journal h-index	IF	CI

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[19] The faculty members working in the area of OM are able to produce more number of papers as compared to those working in other areas such Psychology, Economics, Finance, OB, HRM, Marketing, etc. This is because our basic training in mathematics in India (particularly in IITs, ISIs, IIMs) is at par with best schools in the world whereas in other areas, we stand nowhere near to them. In spite of this advantage, barring a few, surprisingly, most of the faculty members from the OM and DS areas not able to produce papers in top journals.

[20] The lists of top 10 area-wise researchers based on the second and third schemes are available upon request from the authors.

Accounting and Finance (A&F)

1	Bala V Balachandran	Great Lakes	Carnegie Mellon	52	17	1325	51	661.71	1915.14	52.64	1
2	S G Badrinath	IIM Bangalore	Purdue	31	11	1578	17	155.95	619.24	20.63	0.144
3	TT Ram Mohan	IIM Ahmedabad	Stern	35	8	249	31	302.38	483.81	10.46	0.142
4	Jayant R Kale	IIM Bangalore	Univ. of Texas at Austin	28	12	1296	12	153.62	630.93	21.80	0.138
5	Sanjay Kallapur	ISB Hyderabad	Harvard	25	12	1820	12	137.86	412.57	15.62	0.133
6	Rajesh Chakrabarti	ISB Hyderabad	UCLA	16	14	980	16	107.37	433.42	14.04	0.111
7	Srinivasan Rangan	IIM Bangalore	Wharton	17	8	1168	5	67.14	243.29	8.22	0.073
8	V Ravi Anshuman	IIM Bangalore	Univ. of Utah	28	6	771	11	89.05	207.62	7.25	0.069
9	K Subramanian	ISB Hyderabad	Chicago	14	8	542	5	60.02	163.56	7.03	0.056
10	P K Jain	IIT Delhi	Delhi Univ.	32	10	402	14	33.33	142.86	7.02	0.055

Economics

1	Vinish K Kathuria	IIT Bombay	IGIDR	17	17	1160	40	206.02	971.77	31.71	0.204
2	Sajal Ghosh	MDI Gurgaon	N.A.	14	11	777	25	183.93	888.90	41.82	0.177
3	MH Bala Subrahmanya	IISc	ISEC Bangalore	22	13	640	35	141.90	609.24	23.38	0.140
4	Biresh K Sahoo	XIM Bhubaneswar	IIT Kharagpur	16	13	530	24	124.43	866.46	19.53	0.121
5	Ravindra H Dholakia	IIM Ahmedabad	M.S. University	37	9	387	34	149.49	351.92	7.36	0.099
6	Kausik Chaudhuri	IIM Bangalore	State Univ. of New York	18	11	582	22	105.19	503.20	10.83	0.094
7	Morris Sebastian	IIM Ahmedabad	IIM Calcutta	37	12	489	17	138.83	231.67	5.72	0.092
8	Kulbhushan Balooni	IIM Kozhikode	IRMA	18	10	313	23	41.55	448.94	25.02	0.089
9	Rupa Chanda	IIM Bangalore	Columbia Univ.	21	9	990	14	55.05	391.20	17.68	0.088
10	A Damodaran	IIM Bangalore	Univ. of Kerala	28	7	115	12	75.83	391.33	13.71	0.064

Operations Management (OM)

1	C Rajendran	IIT Madras	IIT Madras	25	48	7115	129	528.57	3056.66	83.03	1
1	Ravi Shankar	IIT Delhi	IIT Delhi	16	43	6864	167	218.35	1292.26	57.18	1
3	TT Narendran	IIT Madras	IIT Madras	39	21	2112	63	188.45	948.18	27.44	0.242
4	Vijay Aggarwal	MDI Gurgaon	Case Western Reserve	36	19	1110	22	180.24	803.12	20.77	0.167
5	Gajendra K Adil	IIT Bombay	Univ. of Manitoba	27	12	525	37	185.36	859.14	26.90	0.158
6	Devanath Tirupati	IIM Bangalore	MIT	31	16	1225	32	142.79	573.89	17.78	0.149
7	B Mahadevan	IIM Bangalore	IIT Madras	25	12	1559	21	126.71	740.72	18.82	0.138
8	Devinder Banwet	IIT Delhi	IIT Delhi	23	19	1649	48	31.95	268.73	15.24	0.136
9	G Srinivasan	IIT Madras	IIT Madras	25	12	912	28	119.83	648.75	21.23	0.129
10	LS Ganesh	IIT Madras	IIT Madras	29	16	1328	26	78.61	495.33	16.06	0.125

Decision Sciences (DS)

1	Pulak Ghosh	IIM Bangalore	Oakland	12	19	516	24	170.07	864.30	17.26	0.146
2	U Dinesh Kumar	IIM Bangalore	IIT Bomaby	21	14	816	26	96.71	648.49	19.59	0.121
3	Ishwar Murthy	IIM Bangalore	Texas A&M Univ.	28	8	417	22	138.05	742.49	17.80	0.106
4	T Bandyopadhyay	IIM Ahmedabad	Univ of Calcutta	31	8	172	27	123.36	605.96	13.95	0.092
5	Diptesh Ghosh	IIM Ahmedabad	IIM Calcutta	18	10	474	23	79.78	586.85	15.00	0.090
6	S M Kunnumkal	ISB Hyderabad	Cornell	9	8	212	15	120.71	510.24	14.96	0.086
7	Malay Bhattacharyya	IIM Bangalore	LSE	31	6	141	9	76.67	455.05	10.20	0.079
8	Bhaba K Mohanty	IIM Lucknow	IIT Kharagpur	28	7	188	13	45.12	364.14	12.70	0.057
9	Debjit Roy	IIM Ahmedabad	Wisconsin-Madison	18	7	118	13	62.75	317.72	8.87	0.056
10	Trilochan Sastry	IIM Bangalore	MIT	19	7	207	12	62.143	206.10	5.07	0.054

Organizational Behavior and Human Resources Management (OB&HRM)

1	Ramadhar Singh	IIM Bangalore	Purdue	42	18	1048	70	328.57	2275.07	61.79	0.358
2	Dishan Kamdar	ISB	NUS	11	11	950	14	80.95	588.86	18.22	0.102
3	Noronha Ernesto	IIM Ahmedabad	TISS	21	13	507	26	79.52	206.78	6.89	0.084
4	Jyotsna Bhatnagar	MDI Gurgaon	IIT Delhi	12	15	962	19	34.81	298.64	7.97	0.084
5	Mukta Kulkarni	IIM Bangalore	Univ. of Texas at San Antonio	9	6	560	20	88.17	375.78	16.19	0.083
6	Kanika T. Bhal	IIT Delhi	IIT Kanpur	19	12	443	21	40.12	348.86	12.44	0.075
7	Debashish Bhattacherjee	IIM Calcutta	Univ. of Illinois at Urbana-Champaign	30	10	270	16	109.29	160.52	3.33	0.070
8	Badrinarayan S Pawar	IIM Indore	Oklahoma State Univ.	18	7	768	6	53.33	333.33	14.39	0.069
9	D'Cruz Premilla	IIM Ahmedabad	TISS	14	10	272	16	64.21	196.97	10.31	0.067

	Name										
10	Deepti Bhatnagar	IIM Ahmedabad	IIM Ahmedabad	34	11	670	9	41.15	291.36	9.90	0.067
Management of Information System (MIS)											
1	Indranil Bose	IIM Calcutta	Purdue	19	21	1242	46	254.05	1761.77	55.71	0.298
2	Debashis Saha	IIM Calcutta	IIT Kharagpur	24	18	2034	35	108.53	707.32	31.97	0.190
3	RP Sundarraj	IIT Madras	Univ. of Tennessee	28	14	781	31	171.38	1009.32	32.34	0.171
4	Anand Patwardhan	IIT Bombay	Carnegie Mellon	32	18	1560	27	50.63	464.02	19.30	0.132
5	Sumeet Gupta	IIM Raipur	NUS	9	16	1405	25	65.34	357.83	12.59	0.116
6	Jayanthi Ranjan	IMT Gaziabad	Jamia Millia Islamia	14	11	553	40	26.67	261.79	16.06	0.087
7	Rekha Jain	IIM Ahmedabad	IIT Delhi	27	8	369	11	115.83	339.33	13.50	0.082
8	Praveen R Srivastava	IIM Rohtak	BITS Pilani	7	12	498	22	10.16	204.00	18.76	0.077
9	Kavitha Ranganathan	IIM Ahmedabad	Univ. of Chicago	14	11	1831	6	16.00	184.80	6.23	0.077
10	Ambuj Mahanti	IIM Calcutta	Univ. of Calcutta	32	10	710	19	37.38	321.69	12.66	0.075
	Marketing										
1	Rohit Varman	IIM Calcutta	Univ. of Utah	13	10	451	18	98.67	228.66	11.04	0.083
2	Arpita Khare	IIM Rohtak	Univ. of Allahabad	13	9	206	37	35.62	274.02	16.85	0.077
3	Siddharth S Singh	ISB Hyderabad	Northwestern	13	9	1058	10	52.85	211.84	7.46	0.071
4	Arvind Sahay	IIM Ahmedabad	Univ. of Texas at Austin	19	6	1002	7	57.62	315.52	12.58	0.070
5	Sridhar Samu	ISB Hyderabad	Indiana Univ.	20	8	602	11	51.07	260.95	11.00	0.064
6	Sangeeta Sahney	IIT Kharagpur	IIT Delhi	14	10	620	13	9.40	206.90	9.47	0.056
7	Ramendra Singh	IIM Calcutta	IIM Ahmedabad	7	7	156	21	36.37	223.53	8.46	0.051
8	Dheeraj Sharma	IIM Ahmedabad	Louisiana Tech	11	7	176	16	33.88	229.03	7.97	0.047
9	S Bharadhwaj	Great Lakes	Univ. of Maryland	13	7	182	19	30.71	134.24	5.66	0.044
10	Sinha Piyush Kumar	IIM Ahmedabad	Sardar Patel Univ.	13	10	424	7	12.21	82.50	4.21	0.042
Strategic Management (SM)											
1	P Balachandra	IISc	IISc	25	17	1067	36	167.04	869.18	41.07	0.201
2	Garg Amit	IIM Ahmedabad	IIM Ahmedabad	17	16	1085	35	130.49	1297.94	36.47	0.185
3	RK Pillania	MDI Gurgaon	N.A.	10	13	449	50	89.29	658.80	51.95	0.176
4	PR Shukla	IIM Ahmedabad	Stanford	29	17	855	33	86.43	678.68	25.46	0.140
5	Murali Patibandla	IIM Bangalore	JNU	27	10	535	24	198.21	608.14	13.09	0.124
6	Annapurna Shaw	IIM Calcutta	Univ. of Illinois at Urbana-Champaign	31	9	244	18	183.33	387.67	15.02	0.108
7	Raveendra Chittoor	ISB Hyderabad	IIM Calcutta	8	5	442	8	71.31	302.46	12.39	0.061
8	Shailendra Mehta	IIM Ahmedabad	Harvard	25	10	205	12	49.57	302.31	7.29	0.056
9	Anand Nandkumar	ISB Hyderabad	Carnegie Mellon	9	7	199	4	83.33	275.67	6.89	0.053
10	Sushil Khanna	IIM Calcutta	IIM Calcutta	42	5	102	11	103.33	135.62	2.96	0.050

5. Discussion

The CIs derived through the D-BOD model can be considered as more robust than those derived from the extant BOD models in estimating one's research productivity. As we noted, the CI entailed relative weights of the six criteria objectively generated from the data at hand, and the weights were further corrected by including the directional distance function to avoid any arbitrariness in imposing weight restrictions by the policy analysts. Specifically, our use of the PCA to objectively estimate the directional vector eliminated the arbitrariness problem arising out of the discretionary uses of exogenous directional vectors set by the analysts. Moreover, the D-BOD estimator of efficiency satisfied the 'indication' property

of an ideal efficiency measure well. Accordingly, ours was not only a novel but also an objective approach to estimating the research productivity in B-Schools of India.

There are four key findings. First, the relative weight of the six indicators of journal tier, total citations, IF, author h-index, the number of papers, and journal h-index varied from high to low in order for estimating the CI of a faculty member. Obviously, the most important factor in the estimated research productivity of a faculty member was the tier of the journal in which he or she had published. Second, although both public and private B-Schools were statistically indistinguishable in terms of their research productivity, the B-Schools at IITs outperformed the IIMs that have exclusively been established for management education and research. Third, the aggregate CI allowed us to objectively identify star researchers in India (i.e., those who fell into the top 5% of the distribution according to Schemes I, II, or III). Also, the CIs for 784 faculty members of Scheme I enabled us identify the 10 most accomplished experts in each of the seven areas of management. Finally, the CIs of the faculty members during the most recent 10 years of 2004-2014 led us to identify contemporary star researchers. Interestingly, 40%, 32.5%, 20%, and 7.5% of these stars have been working in IIMs, private B-Schools (i.e., ISB, IMT, MDI, and XIM), IITs, and IISc, respectively. Of them, there were more stars in the public ($n = 27$) than the private ($n = 13$) B-Schools, χ^2 (1, $N = 40$) = 4.90, $p < 0.05$. Apparently, quality publications might have become an important criterion in recent faculty recruitments and/or promotions at the public B-Schools.

Given that the research facilities at IITs and IIMs are nearly the same, why were faculty members at the former seemingly more productive than those at the latter? We can suggest two reasons. One is the difference in the culture. IITs were established as research-intensive institutions; IIMs were training institutes by design. This difference was also corroborated by our finding that the alumni of IITs were more productive than those of IIMs. Second, and no less important, the obtained difference might be a statistical artifact. The number of faculty members at B-Schools of IITs is much lower than that at IIMs. Further, those at IITs might have been recruited based exclusively on the quality of publications and for the tasks of teaching and research. In contrast, faculty members of IIMs are required to have knowledge and skills in training of managers, consulting with clients, advising state and central governments on policy issues, and raising management issues in media in addition to management research [72]. Thus, the difference between IITs and IIMs may be attributed more to a smaller but more homogeneous sample than to any genuine difference in research productivity. This possibility is further corroborated by the result that the number of star researchers at the IIMs according to Scheme III was exactly two times as large as that at the IITs.

Two other results also deserve mention. One was that faculty members who had their doctoral training abroad were more productive over the years than those who were trained in India. Another was that those trained at the IITs were more productive than those trained at the IIMs. Taken together, these differences call attention to the need for further improving the quality of doctoral education in India in general and at the IIMs in particular.

Despite the objectivity in the estimated CI of research productivity, one may still raise objection on the grounds that the length of the published paper and the time spent on completing the research program were totally discounted. One may write a 2-page comment on a paper (or a shorter paper) published in Tier I or Tier II journal but another may write an article of 21 pages [35] and a chapter of 38 pages [73], each based on a decade of programmatic research. Since the study by Singh [73] was published in an edited volume, the importance of this 8-experiment programmatic research conducted over 16 years was not realized until a new volume on the most unloved work in social psychology came out was in 2011 [74]. The very same research resulted in Singh's inclusion on the Association of Psychological Science's website on the *Faces and Minds of Psychological Science* [75]. In contrast, some authors in OM and DS areas had published shorter papers of less than 10 pages in Tier 1 and Tier 2 journals which pushed their CI considerably. Given our focus on journal publications and the six indicators of research productivity, unusual pieces of research [35,73] might have admittedly been underweighted. It is possible, therefore, that our estimates of research productivity could be on a slightly lower side than what they ought to be.

As it is well-known, only basic contributions are cited in the textbooks of a field. Our model did not consider such citations either. Again such omission occurred because of our six indicators of research used in the D-BOD model. Further, the total citations and the author h-index might be underestimated also because the Google Scholar did not perform well for older publications that have not been yet posted on the web [55]. It is possible that Ramadhar Singh's CIs across Schemes I and II might have been underestimated because his 43 papers were published before 1990. Since Singh remained among star researchers across all three schemes, our D-BOD analysis seems to have yielded valid estimates.

We are also aware of differences in the citation patterns across journals of different management areas and hence the resulting wide differences in the IF and h-index values of the journals. For example, some of the OB & HRM journals require citations of only those articles that are of direct relevance for the issues under consideration and even restrict the number of references. Economics, Accounting and Finance, and Marketing, in contrast, encourage citations of all papers on the issue. Such practices have obvious implications for the h-index and IF scores of journals of different fields. Relying on a single

indicator, as Oswald [76] rightly cautioned, might yield a biased estimate of productivity. Precisely because of such danger, our CI estimations included all six indicators, using the D-BOD model.

In sum, it can be said that nearly 94% of the B-Schools in India are still fixated with mere training of younger managers. The positive side that there has been a notable shift in importance from training of managers to advancing management knowledge in at least 6% of the B-Schools in the recent 10 years. Nevertheless, there are still considerable differences between faculty members of different areas. Given adequate time and resources for research in all areas as suggested previously [9,10], the IIMs at Ahmedabad, Bangalore, and Calcutta; the IITs at Bombay, Delhi, and Madras; the IISc at Bangalore; and two private B-Schools (i.e., ISB Hyderabad, MDI Gurgaon) can be expected to generate impactful management knowledge in the future.

6. Suggestions for accelerating research productivity

In order to accelerate research productivity in India, B-Schools of India need to satisfactorily address to three important issues of (1) quality of the doctoral programs, (2) self-renewals of the faculty members, and (3) research programs by the stars identified.

1) Faculty members who had their doctoral degrees from abroad and/or had worked abroad for a few years were more productive than those who had such degree or experience exclusively in India. To us, this difference does point to the inadequacy in the indigenous doctoral programs. In addition to further strengthening the doctoral programs, it may be proper to annually support advanced degree of at least 50 young Indian scholars abroad. Whenever there is an opportunity for faculty exchange between Indian and foreign schools, such opportunity should also be availed of.

2) The doctoral programs at the IIMs should provide students with opportunities to be mentored by faculty members who are themselves active and productive in research. In addition, students admitted to a doctoral program should be required to publish at least two papers in peer-reviewed international journals before submitting their doctoral dissertations. This requirement should be even stricter for those who had not written an honors or master's thesis before joining the doctoral program.

3) One's doctoral training has a life cycle of no more than 5-6 years. In order to be a good mentor or research supervisor, therefore, the faculty member has to more knowledgeable than the student supervised. This goal can be achieved only when faculty members have been leading a research program. Research programs facilitate mentoring of younger scholars as well as self-renewal of the faculty members themselves. While younger faculty members should be given more time and

support for running a research program, the tenured ones should be required to go on sabbatical leave to a reputed school to recharge themselves with the advances in literature and method of their specialization.

Acknowledgement

References

[1] http://pmindia.gov.in/en/news_updates/text-of-pms-address-at-the-102nd-indian-science-congress/

[2] http://www.aicte-india.org/foreignuniversities.php

[3] http://www.livemint.com/Politics/JtHPA61PdLaQIzSxtwgZUI/Foreign-universities-open-India-centres.html

[4] http://www.timeshighereducation.co.uk/world-university-rankings/2014-15/subject-ranking/subject/social-sciences

[5] http://jindal.utdallas.edu/the-utd-top-100-business-school-research-rankings/

[6] http://www.shanghairanking.com/

[7] https://www.iimcal.ac.in/iims-meet-goa-discuss-emerging-issues-management

[8] http://www.ndtv.com/india-news/iit-iim-faculty-not-world-class-jairam-ramesh-456533

[9] http://timesofindia.indiatimes.com/city/ahmedabad/Sibal-defends-IIM-IIT-faculty/articleshow/8576121.cms

[10] Kumar N. Taking stock of Indian management research. Economic Times (http://economictimes.indiatimes.com/opinion/view-point/taking-stock-of-indian-management-research/articleshow/7440640.cms)

[11] Publish or Perish. Economic Times (http://articles.economictimes.indiatimes.com/2011-02-08/news/28425879_1_business-schools-paper-research)

[12] Khatri N, Ojha AK, Budhwar P, Srinivasan V, Varma A. Management research in India: current state and future directions. IIMB Management Review 2012; 24: 104-15.

[13] Singh R. Sloppy research versus disinterest in Indian data as a difficulty factor in international publications. Pan IIM World Management Conference, IIMK, November 5, 2014. http://www.iiimb.ernet.in/webpage/ramadhar-singh

[14]   Kumar N. Indian Business schools still display pre-reforms mentality. Economic times(http://economictimes.indiatimes.com/opinion/view-point/indian-business-schools-still-display-pre-reforms-mentality/articleshow/8138503.cms)

[15]   Madhavan N. Paper Lambs. Business Today, October 28, 2012 edition, (http://businesstoday.intoday.in/story/best-b-school-research-lag/1/188766.html)

[16]http://articles.economictimes.indiatimes.com/2012-07-03/news/32523925_1_iim-calcutta-iim-a-alumni-association-iim-bangalore

[17]http://www.iimidr.ac.in/iimi/images/IIM_INDORE_OVER_THE_YEARS/RULESREGULATIONSPART-2.pdf

[18]   Hsieh P-N, Chang, P-L. An assessment of world-wide research productivity in production and operations management. Int J Prod Econ 2009; 120: 540-51.

[19]   Malhotra MK, Kher HV. Institutional research productivity in production and operations management. J Oper Manag 1996; 14: 55-77.

[20]   Hsieh P-N. Addendum to "an assessment of world-wide research productivity in production and operations management". Int J Prod Econ 2010; 125: 135-38.

[21]   Young ST, Baird BC, Pullman ME. 1996. POM research productivity in US business schools. J Oper Manag 1996; 14: 41–53.

[22]   Liu JS, Lu, LYY, Lu W-M, Lin BJY. Data envelopment analysis 1978–2010: a citation-based literature survey. Omega-Int J Manage S 2013; 41: 3-15.

[23]   Ansari A, Lockwood D, Modarress B. Characteristics of periodicals for potential authors and readers in production and operations management. Int J Oper Prod Manage, 1992; 12: 56-65.

[24]   Barman S, Hanna MD, LaForge RL. Perceived relevance and quality of POM journals: A decade later. J Oper Manag 2001; 19: 367-85.

[25]   Barman S, Tersine R, Buckley MR. An empirical assessment of the perceived relevance and quality of POM related journals by academicians. J Oper Manag 1991; 10: 194-210.

[26]   Olson JE. Top-25-business-school professors rate journals in operations management and related fields. Interfaces 2005; 35: 323-38.

[27]   Soteriou AC, Hadjinicola GC, Patsia K. Assessing production and operations management related journals: the European perspective. J Oper Manag 1999; 17: 225-38.

[28]   Mingers J, Leydesdorff L. A review of theory and practice in Scientometrics. Eur J Oper Res (2015), doi: 10.1016/j.ejor.2015.04.002

[29]   Lawrence, PA. The mismeasurement of science. Curr Biol 2007; 17: 583-85.

[30] Singh R. Reinforcement and attraction: Specifying the effects of affective states. J Res Pers 1974; 8: 294-305.

[31] Singh R. Information integration theory applied to expected job attractiveness and satisfaction. J Appl Psychol 1975; 60: 621-23.

[32] Singh R. Leadership style and reward allocation: does least preferred co–worker scale measure task and relation orientation? Organ Behav Hum Perf 1983; 32: 178-97.

[33] Singh R. A test of the relative ratio model of reward division with students and managers in India. Genet Soc Gen Psych 1985; 111: 363-84.

[34] Singh R. "Fair" allocations of pay and workload: tests of a subtractive model with nonlinear judgment function. Organ Behav Hum Dec 1995; 62: 70-78.

[35] Singh R. Subtractive versus ratio model of "fair" allocation: Can group level analyses be misleading? Organ Behav Hum Dec 1996; 68: 123-44.

[36] Singh R. Group harmony and interpersonal fairness in reward allocation: on the loci of the moderation effect. Organ Behav Hum Dec 1997; 72: 158-83.

[37] Singh R, Simons JJP, Self, WT, Tetlock PE, Zemba Y, Yamaguchi S, et al. Association, culture, and collective imprisonment: Tests of a causal-moral model. Basic Appl Soc Psych, 2012; 34: 269-77.

[38] Singh R, Wegener DT, Singh S, Sankaran K, Lin PKF, Seow MX, et al. On the importance of trust in interpersonal attraction from attitude similarity. J Soc Pers Relat 2015 (in press).

[39] Greenberg R, Nunamaker TR. A generalized multiple criteria model for control and evaluation of nonprofit organizations. Financial Accountability and Management, 1987; 3: 331-42.

[40] Barrow M, Wagstaff A. Efficiency measurement in the public sector: an appraisal. Fisc Stud 1989; 10: 72-97.

[41] Cherchye L, Ooghe E, Van Puyenbroeck T. Robust human development rankings. J Econ Inequal 2008b; 6: 287-321.

[42] Sahoo BK, Acharya D. An alternative approach to monetary aggregation in DEA. Eur J Oper Res 2010; 204: 672-82.

[43] Sahoo BK, Acharya D. Constructing macroeconomic performance index of Indian states using DEA. J Econ Stud 2012; 39: 63-83.

[44] Melyn W, Moesen W. Towards a synthetic indicator of macroeconomic performance: unequal weighting when limited information is available. Public Economics Research Paper 17, 1991; Centre for Economic Studies, Leuven.

[45] Oral M, Oukil A, Malouin, J-L, Kettani O. The appreciative democratic voice of DEA: a case of faculty academic performance evaluation. Socio Econ Plan Sci 2014; 48: 20-28.

[46] Dyson RG, Allen R, Camanho AS, Podinovski VV, Sarrico CS, Shale EA. , 2001. Pitfalls and protocols in DEA. Eur J Oper Res 2001; 132: 245–59.

[47] Jones MJ, Brinn T, Pendlebury M. Journal evaluation methodologies: a balanced response. Omega-Int J Manage S 1996; 24: 607-12.

[48] Frey BS, Rost K. Do rankings reflect research quality? J Appl Econ 2010; 13: 1-38.

[49] Halkos GE, Tzeremes NG. Measuring economic journals' citation efficiency: a data envelopment analysis approach. Scientometrics 2011; 88: 979-1001.

[50] Tüselmann H, Sinkovics RR, Pishchulov G. Towards a consolidation of worldwide journal rankings – a classification using random forests and aggregate rating via data envelopment analysis. Omega-Int J Manage S 2015; 51: 11-23.

[51] Hult GTM, Reimann M, Schilke O. Worldwide faculty perceptions of marketing journals: rankings, trends, comparisons, and segmentations. GlobalEDGE Business Review 2009; 3: 1-23.

[52] Baum JAC. Free-riding on power laws: questioning the validity of the impact factor as a measure of research quality in organization studies. *Organization* 2011; 18: 449-66.

[53] Kulkarni, AV, Aziz B, Shams I, Busse JW. Comparisons of citations in web of science, Scopus, and Google scholar for articles published in general medical journals. JAMA 2009; 302: 1092-96.

[54] Vaughan L, Shaw D. A new look at evidence of scholarly citations in citation indexes and from web sources. *Scientometrics*, 2008; 74: 317-30.

[55] Meho LI, Yang K. A new era in citation and bibliometric analyses: web of science, scopus, and google scholar. J Am Soc Inf Sci Tec 2007; 58: 2105-25.

[56] Kousha K, Thelwall M. Google scholar citations and google web/url citations: a multi-discipline exploratory analysis. J Am Soc Inf Sci Tec 2007; 58: 1055-65.

[57] Kousha K, Thelwall M. (2008) Sources of google scholar citations outside the science citation index: a comparison between four science disciplines. Scientometrics, 2008; 74: 273-94.

[58] Harzing A-W. Google scholar – a new data source for citation analysis. http://www.harzing.com/pop_gs.htm

[59] Cooper WW, Seiford LM, Tone K. Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software, New York: Springer, 2007.

[60] Zhu J. Quantitative models for performance evaluation and benchmarking: data envelopment analysis with spreadsheets, New York: Springer, 2014.

[61] Alchian AA. Some economics of property rights. *Il Politico* 1965; 30: 816-29.

[62] De Alessi L. The economics of property rights: a review of the evidence. In: Richard OZ, Editor. Research in law and economics: a research annual, Greenwich, C. T.: Jai Press; 1980, vol. 2, p. 1-47.

[63] Cherchye L, Vermeulen F. Robust rankings of multidimensional performances: an application to tour de France racing cyclists. J Sport Econ 2006; 7: 359-73.

[64] Munda G, Nardo M. Noncompensatory/nonlinear composite indicators for ranking countries: a defensible setting. Appl Econ 2009; 41: 1513-23.

[65] Fusco E. Enhancing non-compensatory composite indicators: a directional proposal. Eur J Oper Res 2015; 242: 620-30.

[66] Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. Eur J Oper Res 1978; 2: 429-41.

[67] Podinovski VV. Criteria importance theory. Math Soc Sci 1994; 27: 237-52.

[68] Chambers RG, Chung Y, Färe R. Profit, directional distance functions, and Nerlovian efficiency. J Optimiz Theory App 1998; 98: 351-64.

[69] Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage Sci 1984; 30: 1078-92.

[70] Sahoo BK, Mehdiloozad M, Tone K. Cost, revenue and profit efficiency measurement in DEA: a directional distance function approach. Eur J Oper Res 2014; 237: 921-31.

[71] Mehdiloozad M, Sahoo BK, Roshdi I. A generalized multiplicative directional distance function for efficiency measurement in DEA. Eur J Oper Res 2014; 232: 679-88.

[72] Government of India. Report of IIM review committee, negotiating the big leap - IIMs: from great teaching institutions to thought leadership centres, 25 September 2008. Available at http://mhrd.gov.in/sites/upload_files/mhrd/files/document-reports/bhargava_IIMreview_0.pdf

[73] Singh, R. Two problems in cognitive algebra: Imputations and averaging–versus–multiplying. In: Anderson NH, Editor. Contributions to information integration theory, Hillsdale, NJ: Erlbaum; 1991, vol. II, pp. 143-80.

[74] Singh, R. Imputing values to missing information in social judgment. In: Arkin RM, Editor. Most underappreciated: 50 prominent social psychologists describe their most unloved work, New York: Oxford University Press; 2011, pp. 159-64.

[75] http://www.psychologicalscience.org/index.php/members/psychological-scientists#singh

[76] Oswald A. An examination of the reliability of prestigious scholarly journals: evidence and implications for decision-makers. Economica 2007; 74: 21-31.