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

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

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**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 102$^{nd}$ 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

[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

[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 $i^{th}$ 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 × 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 $r^{th}$ indicator $(r \in R = \{1, 2, ..., 6\})$ for a faculty member $j$, $j \in J$ was computed as:

$$I_{rj}^{n} = \frac{I_{rj} - \underline{I}_{r}}{\overline{I}_{r} - \underline{I}_{r}}, \tag{1}$$

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

[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 $r^{th}$ normalized indicator by the $j^{th}$ faculty member, the CI of research productivity for a faculty member $j$ $(\mathrm{CI}_j)$ thus became

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

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.

[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 $o$ $(\mathrm{CI}_o^{BOD})$ as measured by output efficiency parameter $\theta$.[12] Here, $\mathrm{CI}_o^{BOD}$ lies between 0 (worst performance) and 1 (best performance). Symbolically, $0 < \mathrm{CI}_o^{BOD} \leq 1$. 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

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

[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] $\mathrm{CI}_o^{BOD} = \max_{\theta,\lambda} \theta$ 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 $\beta_r$ represents the rate of maximum improvement in the $r^{th}$ indicator of faculty member $o$ . Thus, the higher the value of $\beta$ , 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 $\mathrm{CI}_o^{D-BOD} = 1$. Technically, $0 < \mathrm{CI}_o^{D-BOD} \leq 1$.

The technology structure employed in the *D-BOD* model (3) uses $\lambda$ as weights to form a linear combinations of $N$ observed faculty members. Here the variable $\lambda$ (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 $\lambda$ 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 $\mathrm{CI}_o^{D-BOD}$ by looking at the maximum possible improvements in each and every individual indicator represented by $\beta_r$ $(r \in R)$. Each improvement parameter $\beta_r$ carried a weight in term of its relative importance, i.e.,$\left( g_r / G \right)$. The weighted sum, i.e., $\sum_{r \in R} \left( g_r / G \right) \beta_r$ 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 $1 \Big/ \left( 1 + \sum_{r \in R} \left( g_r / G \right) \beta_r \right)$. 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.

[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

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

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 $\mathrm{var}(\hat{I}_{pc1})$ represents the kernel variance of the projected value of $I_1$ onto the PC, $\hat{I}_{pc1}$; $\mathrm{var}(\hat{I}_{pc2})$ 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., $\mathrm{var}(\hat{I}_{pc2}) / \mathrm{var}(\hat{I}_{pc1})$) 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 $\beta$ 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 *Scopus*). 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.

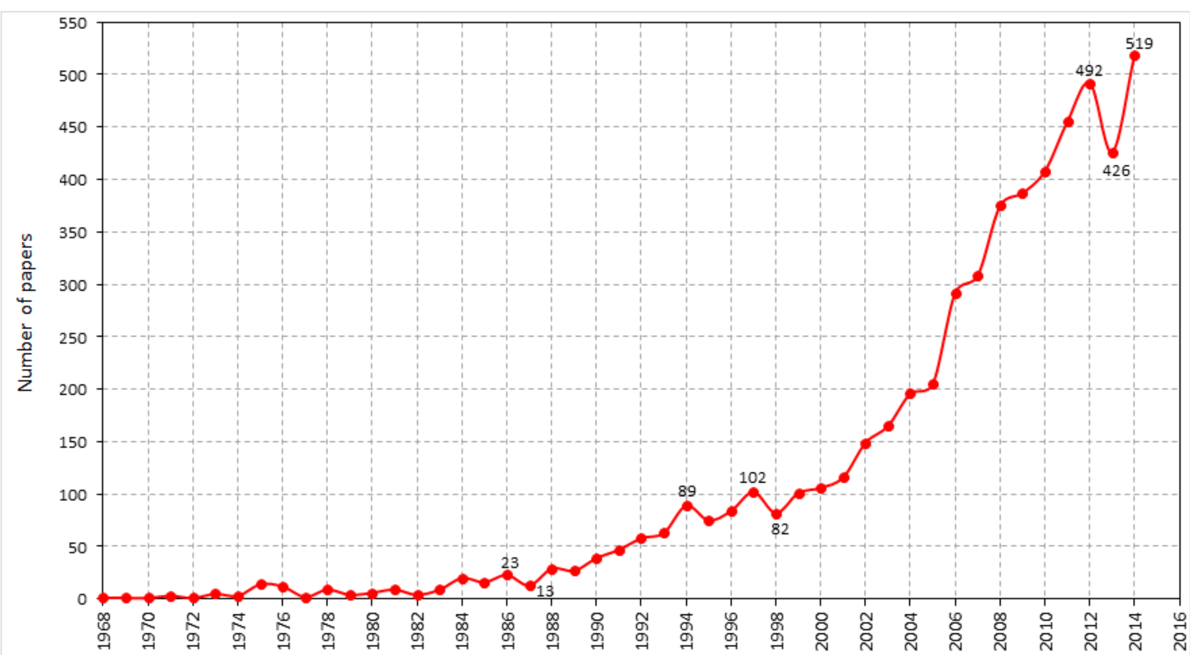


**Fig. 1.** Distribution of published papers over years.

### 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 (*M*s), Standard Deviations (*SD*s), and range of research productivity as revealed by each of the six indicators.

**Table 1. *M*s, *SD*s, 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, *t*s (782)

$\geq 1.703$, $p$s $\leq 0.05$. Among the public B-schools, however, the non-IIM schools outperformed the IIMs only on two indicators - author $h$-index and number of paper, $t$s $(548) \geq 2.421$, $p$s $< 0.01$; but not on the other four indicators, $t$s$(548) \leq 1.551$, $p$s $\geq .06$.

**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, 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 |

[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. *M*s, *SD*s, 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 *M*s 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

[15] The top three *M*s of Table 2 were essentially due to one superstar in each business school. When we removed such an outlier, the *M*s 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 *SD*s of 0.0372, 0.0128, and 0.0620. These new *M*s 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)**

[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

[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

[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 |
|---|---|---|---|---|---|---|---|---|---|---|---|

[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.

| | | | | (years) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **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 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 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, $\chi^2(1, N = 40) = 4.90, p < 0.05$. 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.

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