# Discussion Papers in Economics

## Science Research and Knowledge Creation in Indian Universities: Theoretical Perspectives and Econometric Evidence

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August 2015

Discussion Paper 15-10

Centre for International Trade and Development

School of International Studies

Jawaharlal Nehru University

India

# Science Research and Knowledge Creation in Indian Universities: Theoretical Perspectives and Econometric Evidence

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***Abstract***

In this paper, we present an economic analysis of science research and knowledge creation in Indian universities. We posit that faculty's research effort is an outcome of her optimum time allocation decision, which in turn shapes knowledge creation in universities. Accordingly, the present paper has a two-fold objective: (1) to develop a theoretical model of research effort by academic scientists in India, and (2) to estimate the research production function that transforms research effort into knowledge outputs controlling for various other factors, using tools of applied econometrics. We establish, theoretically as well as empirically, that contrary to the fairly well accepted proposition of declining research effort/productivity over a scientist's life cycle in the western world, Indian academic scientists, *ceteris paribus*, tend to devote a larger share of their time to research and produce larger volumes of research output over their lifetime.

***Acknowledgement***

We are grateful to Christine Greenhalgh, Saradindu Bhaduri, K L Krishna and Ashok Guha for their substantive comments.

Key words:
Academic Research, Knowledge Creation, Indian Universities, Research Production Function

JEL: O31, O34, O38, I23

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## I. Introduction

Knowledge based sectors have played an important role in India's economic emergence in the recent decades, thanks to India's concerted policy thrust on university education (especially in science and technology) in its post colonial development strategy. At present, there is a renewed policy interest to energise research and knowledge creation in Indian universities so that it can play a pivotal role in ushering in creativity and innovativeness to transform India into a vibrant knowledge driven economy and society. However, there is very little by way of an analytical understanding of the process of university research and knowledge creation in India. The issue has remained unexplored even by the relatively large body of multidisciplinary Indian scholarship on innovation studies. In this paper, we present an economic analysis of science research and knowledge creation in Indian universities.

Academia, the world over, is mandated to create and impart knowledge, broadly reflected in its primary activities of research and teaching.[1] In this paper, we focus only on *knowledge creation* arising out of university research by academic scientists. Academic scientists work in a multi-tasking environment that include teaching, research (and supervision), administrative duties, industry interface and knowledge transfer through formal and informal channels. Despite these diverse claims on faculty's time, research for knowledge creation remains a prime activity of university faculty everywhere.

Although, the Indian academia is also characterised by similar norms and practices, we would like to highlight three dimensions that distinguishes it to some extent from the western academic environment, particularly that of the USA. First, academia in India enjoys near total government patronage – not only are universities publicly funded, most research projects therein are funded by government sources.[2] Second, human capital generation is a primary goal of Indian universities and teaching is perceived to be very important. And third, Indian academia has remained somewhat distant from the industry. Scientists' research rarely leads to income generating assets. It is only recently (in the last decade or so) that concerns regarding taking university research to the marketplace have started featuring prominently in academic management. Naturally, patenting of faculty research has been somewhat random and sporadic till now. It is in this context that we intend to model research effort and knowledge creation by academic scientists in India.

We posit that faculty's research effort is an outcome of her optimum time allocation decision, which in turn shapes knowledge creation in universities. While the time allocation problem is essentially a theoretical question, how research effort determines knowledge creation may be posed as an empirical issue. Accordingly, the present paper has a two-fold objective: (1) to examine the process of knowledge creation in Indian universities by providing a theoretical understanding of research effort in the context of Indian academia, and (2) an econometric estimation of the research production function that transforms research effort into knowledge outputs controlling for various other factors.[3]

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[1] According to Nelson (1986), the role of the university as disseminator of public knowledge is distinct from its role as creator of new public knowledge, the rhetoric of strong complementarities in research and teaching notwithstanding.

[2] Only in the very recent years private universities have started coming up in India.

[3] Indian academia is characterised by significant heterogeneity in terms of infrastructure and quality of research and hence the drivers of knowledge creation are likely to vary widely across the quality spectrum. In this paper, we focus only on the top tier of Indian academia for our theoretical and econometric analyses. The insights derived from our results should not be generalised for the entire quality spectrum of Indian academia.

There are a handful of studies, mostly in the context of the US academia[4] (none for India), that have modelled faculty research behaviour both theoretically and empirically. All of them establish a declining research effort/productivity over a scientist's life cycle. We intend to take a re-look at this proposition, theoretically and empirically, in the context of Indian academia. We divide the paper into four sections. After this introduction, section II presents a theoretical model of faculty research effort in the Indian context. We arrive at four propositions from the theoretical results. This is followed by an econometric estimation of the research production function in section III. The objective is not only to confirm some of the propositions derived in section II, but also to extend the scope of our analysis beyond the theoretical model in order to come up with a comprehensive understanding of the drivers of knowledge creation in Indian academia. Section IV presents our concluding remarks.

## II. Faculty Research Effort – theoretical perspectives

To model faculty research effort as an inter-temporal time allocation problem, we follow the conventional models of life cycle behaviour a la Levin and Stephan (1991) and Thursby et al (2007). In our model, we capture how faculty optimally allocates her fixed endowment of time to two competing activities of *teaching* and *research* in each period over their lifetime. Although faculty members have institutionally fixed teaching load, we expect that commitment to teaching goes beyond fixed lecture hours, as time devoted to lecture preparations augments lecture quality and teaching performance. To simplify, we club research and research supervision together as there may be near invisible partition between these two activities. We also ignore administrative duties and industrial consultancies from our time allocation problem.[5]

To construct a model of inter-temporal allocation of faculty time between research and teaching, it is necessary to understand the underlying motivations and reward structures that drive science research. Economists tend to believe that scientists, like any other economic agent, are essentially driven by the attraction of financial rewards arising out of their research outcomes. However, in the 'Mertonian' world of scientific research (Merton 1957, 1973, Dasgupta and David 1994, Stephan 1996), the goal of scientists is to establish priority of discovery by being the first to communicate an advance in knowledge and the rewards are in the form of recognition awarded by the scientific community through eponymy, prestigious prizes and citations. Yet another motivation arises out of the intrinsic satisfaction that scientists derive in solving interesting and challenging research puzzles (Hagstrom 1965, Hull 1988).[6] We would like to club recognition with joy of research as the so-called *consumption motivation* for research, as opposed to the *investment motivation* linked only to financial rewards. Lam (2011) finds that a 'great majority' of scientists are motivated by recognition and joy of puzzle-solving and only a 'small minority' are driven by financial rewards.

[4] For instance, Diamond Jr. (1984), Levin and Stephan (1991), Thursby et al (2007). A second group of studies like Hall et al (2007), Turner and Mairesse (2003), Kelchetermans and Veugelers (2011, 2013) empirically investigate the European context in this regard. However, contrary to earlier evidence of declining research productivity over faculty's life time, the latter studies apparently do not endorse such age effects.

[5] Administrative tasks come in the form of obligations, not entirely driven by her own decision making. Insofar as consultancy is concerned, though not entirely sporadic, it does not in general constitute a significant portion of the academic portfolio of the Indian faculty (of course with some noted exceptions). Moreover, faculty members engaged in industrial consultancies often consider it to be an integral part of their research activity itself.

[6] To quote Hagstrom (1965, p. 16), "Research is in many ways a kind of game, a puzzle solving operation in which the solution of the puzzle is its own reward."

Stephan (1996) is candid is acknowledging the lack of credibility of economic models built on investment motivation for research. Indeed, Levin and Stephan (1991) did incorporate a consumption motivation (over and above the investment motivation) in their model, but arrived at the same conclusion of declining research productivity over a finite career span as commonly established in investment motivation driven models.

In the context of Indian academia, the investment motivation is likely to be even weaker, if not absent. Research is *not* considered by university faculty in India as an investment decision to generate future financial rewards. This is primarily because the scope of financial gains from academic research outputs is extremely limited in India. Rarely any university research in India has found its way to the marketplace, yielding any significant financial reward to the faculty (Ray and Saha, 2012). Industry and academia have remained in splendid isolation from each other till date. Therefore, the mindset of the Indian academic scientists remains untarnished by the lure of 'gold' a la Lam (2011). One may also argue that academia is definitely not one of the best paid professions in India (as in many other countries perhaps) and given that university faculty has already made a conscious choice of this profession, they are unlikely to be driven by monetary considerations in pursuing their academic activities. Evidence from the dataset that we generated for our econometric analysis supports this mindset of the Indian academia.[7] Accordingly, in this paper, we consider only the *consumption motivation* for academic research to model university scientist's optimum path of lifetime research effort in India. Our econometric analysis will entail a more rigorous confirmation of the validity of this assumption.

We conceptualise faculty research as a production process, where research effort (time devoted to research) is transformed into research output in a monotonic fashion. Traditionally, life cycle models of faculty research behaviour have ignored the overwhelming importance of teaching in potentially influencing faculty research behaviour, which we try to incorporate in our model. We argue that teaching (quality and quantity) augments research. This could be because, teaching provides the faculty member with the scope and opportunity to sharpen and continuously question her academic understanding through repeated lectures. In the process she acquires greater clarity on the subject that helps her identify impending research puzzles with a solution concept to start with. We may conceptualise this as *accumulated personal knowledge*, generated through her past teaching, which enters the research production function.[8] As a result, faculty is bound to face a time allocation trade-off between teaching and research over life time.

Finally, we argue that there may be a negative effect associated with research effort (research time) on research production due to the following reasons. First, research is inherently uncertain and hence part of the research effort may get dissipated without leading to any tangible research outcomes. Secondly, insofar as research is viewed as knowledge creation, we must acknowledge the fact that knowledge depreciates over time (loosing relevance/obsolescence of research outputs). Notionally, a part of the research effort goes into maintaining the knowledge stock without creating any new research output. This fraction of

[7] Most respondents (over 90%) do not engage in income generating consultancies in any significant manner – 60% report no consultancy and over 30% spend less than 10% of their time on consultancies. 90% of respondents do not have any clear preference for private funding of research that usually entails private financial gains in terms of honorariums. For 66% of respondents, financial gain is not a motivation to patent their research. And finally, peer recognition and dissemination are the dominant motives for publication.

[8] Arguably, faculty's past research (at least a part of it) could also augment the stock of her accumulated personal knowledge.

research time has to be deducted from the research production function.

Using optimal control theory, we model a dynamic adjustment path for research and teaching effort (captured by the share of time devoted to these two activities) over the lifetime of a typical university faculty member, who is set out to maximize her lifetime research output specified in terms of a research production function.[9] We specify the following instantaneous quasi-linear research production function $v(\cdot)$ for a university faculty member, where $v(\cdot)$ is assumed to be twice differentiable and concave:

$$v(p_t, I_t \mid \alpha, \beta, \delta) = \ln(1-p_t)^{\alpha} + \beta I_t - \delta(1-p_t) \tag{1}$$

Here, $p_t$ is the fraction of time devoted to teaching (preparation time for class lectures including actual class hours), and hence $(1-p_t)$ is the fraction of time devoted to research. $I_t$ is conceptualised as accumulated personal knowledge in period $t$ acquired through past teaching (and research) and $\alpha$, $\beta$ and $\delta$ are parameters ( $>0$ ) defining the model. The faculty research production function has three components. The first component $(1-p_t)^{\alpha}$ represents monotonic transformation of research time into research output, where $\alpha$ captures faculty's research ability (marginal productivity of research time). The second component $\beta I_t$ represents the spillover effects of accumulated personal knowledge on research output, and the third component $\delta(1-p_t)$ is the negative effect associated with research effort. Faculty member's decision making in each period lies in optimally distributing work hours into teaching and research. The *control variable* for the problem therefore is the time devoted to teaching (or conversely, to research) denoted by $p_t$ (or conversely, $1-p_t$).

The constraint faced by the faculty member in maximising her lifetime research output, is the changing stock of $I_t$ over her career span. $I_t$ is the *state variable* in our optimal control problem. We characterise the dynamic path $I_t$ of as:

$$\dot{I}_t = p_t + \rho(1-p_t) - \gamma I_t \tag{2}$$

where, $\dot{I}_t$ is the rate at which $I_t$ gets augmented overtime. $I_t$ is augmented by time devoted to teaching ( $p_t$ ) and a fraction ($\rho$) of time devoted to research $(1-p_t)$. Also, $I_t$ is expected to gradually erode over time and this is captured by the parameter $\gamma$ in the specification of $\dot{I}_t$.

The problem is to

Maximise $\quad V = \int_0^{T} e^{-rt}[\ln(1-p_t)^{\alpha} + \beta I_t - \delta(1-p_t)]dt$

subject to $\quad \dot{I}_t = p_t + \rho(1-p_t) - \gamma I_t,$

$\quad 0 < p_t < 1$

[9] Absence of consumption good in the objective function is a deviation from standard lifetime models. We do not incorporate any explicit income generating or asset forming process in our analysis – investment motives behind teaching and research activities are assumed away.

$$I(0) = 0$$
$$I(\mathrm{T}) \text{ is free}$$
$$\alpha, \beta, \delta, \gamma > 0, \; 0 < \rho < 1$$

where $V$ is faculty's lifetime research output (assuming the value function to be inter-temporally additive) and $r$ is the rate of time preference. We assume that the terminal time T is fixed and $r$ is zero[10], the initial level of teaching is zero ($I(0) = 0$) and the terminal level of teaching is not restricted i.e. $I(\mathrm{T})$ is free.

The Hamiltonian function is:

$$H = \alpha \ln(1 - p_t) + \beta I_t - \delta(1 - p_t) + \lambda[p_t + \rho(1 - p_t) - \gamma I_t] \quad (3)$$

where, $\lambda$ is the co-state variable denoting the shadow price of accumulated personal knowledge.

The solution to the problem requires that the Hamiltonian be maximised with respect to the control variable at every point in time.

$$\frac{\partial H(I_t^*, p_t^*, \lambda_t, t)}{\partial p_t} = 0 \quad (4)$$

The maximum principle for optimal control problems leads to a canonical system that involves two first order differential equations in the state variable and the co-state variable (equations 5 and 6). The maximum principle ensures $p_t^*$ maximizes $\int_0^{\mathrm{T}} v(I_t, p_t, t)dt$ allowing interior solution in the admissible region of the control variable. Equation 7 is the transversality condition for the free-terminal-state problem; one with a vertical terminal line.

$$\frac{\partial H(I_t^*, p_t^*, \lambda_t, t)}{\partial I_t} = -\dot{\lambda}_t \quad (5)$$

$$\frac{\partial H(I_t^*, p_t^*, \lambda_t, t)}{\partial \lambda_t} = \dot{I}_t \quad (6)$$

$$\lambda(\mathrm{T}) = 0 \quad (7)$$

Equations 4 and 5 give us the following

$$p_t^* = \frac{\delta - \alpha + \lambda_t(1 - \rho)}{\delta + \lambda_t(1 - \rho)} \quad (8)$$

$$\lambda(t) = Ae^{\gamma t} + \frac{\beta}{\gamma} \quad (9)$$

(This is obtained as a general solution of the differential equation 5: $\dot{\lambda} - \gamma\lambda = -\beta$)

[10] We assume that individual faculty members treat current and future values of utility equally (i.e. they attach similar weights to both). She does not discount future possible utilities while allocating her 'effort'.

To find the particular solution of the above equation we need to know the value of the constant $A$ and hence we need the transversality condition (equation 7). In this case, since $I_{\mathrm{T}}$ is free, $\lambda(\mathrm{T})$ is zero. Therefore, with the given boundary condition we obtain

$$A = -\frac{\beta}{\gamma} e^{-\gamma \mathrm{T}} \tag{10}$$

Substituting the value of $A$ in (9) gives us the particular solution as

$$\lambda(t) = \frac{\beta}{\gamma}[1 - e^{-\gamma(\mathrm{T}-t)}] \tag{11}$$

The solution for $p_t^*$ in this optimal control exercise is given by:

$$\begin{aligned} p_t^* &= \frac{\gamma(\delta - \alpha) + \beta(1-\rho)\{1 - e^{-\gamma(\mathrm{T}-t)}\}}{\gamma\delta + \beta(1-\rho)\{1 - e^{-\gamma(\mathrm{T}-t)}\}} \\ &= 1 - \gamma\alpha[\gamma\delta + \beta(1-\rho)\{1 - e^{-\gamma(\mathrm{T}-t)}\}]^{-1} \end{aligned} \tag{12}$$

PROPOSITION 1: *Research activity increases over life time*

$$\frac{\partial p_t^*}{\partial t} = -\frac{\alpha\beta(1-\rho)\gamma^2 e^{-\gamma(\mathrm{T}-t)}}{[\gamma\delta + \beta(1-\rho)\{1 - e^{-\gamma(\mathrm{T}-t)}\}]^2} < 0 \qquad \textit{for } t < \mathrm{T}$$

In other words, $p_t^*$ shows a declining path over time, confirming that faculty tends to devote less time to teaching and an increasing share of time to research over the life cycle. This is contrary to the results obtained by Levin and Stephan (1991) and Thursby et al (2007) which established that research activity of university scientists declines over the life cycle. However, our result is consistent with the commonly held belief that Indian academics tend to devote more time to teaching over research in their initial years (beginning of the career), even if there is no bias against junior faculty in the allocation of teaching load. This proposition requires empirical validation.

PROPOSITION 2: *Research productivity augments research activity*

$$\frac{\partial p_t^*}{\partial \alpha} = -\frac{\gamma}{\gamma\delta + \beta(1-\rho)[1 - e^{-\gamma(\mathrm{T}-t)}]} < 0 \qquad \textit{for } t < \mathrm{T}$$

Higher marginal productivity of research (α), reflecting initially fixed levels of faculty's research ability, leads to greater research effort. In essence, a more competent scientist will devote a larger fraction of her time to research.

PROPOSITION 3: *Higher spillovers from teaching reduces research activity*

$$\frac{\partial p_t^*}{\partial \beta} = \frac{\gamma\alpha(1-\rho)[1 - e^{-\gamma(\mathrm{T}-t)}]}{[\gamma\delta + \beta(1-\rho)(1 - e^{-\gamma(\mathrm{T}-t)})]^2} > 0 \qquad \textit{for } t < \mathrm{T}$$

A higher value-coefficient of spillover effects of teaching on research (β) results in a higher share of time devoted to teaching.

PROPOSITION 4: *Higher dissipation of research effort reduces research activity*

$$\frac{\partial p_t^*}{\partial \delta} = \frac{\alpha \gamma^2}{[\gamma\delta + \beta(1-\rho)(1-e^{-\gamma(\mathrm{T}-t)})]^2} > 0 \qquad for\ t < \mathrm{T}$$

Given the additive form of the objective function in our lifetime model reflecting a possible substitution between teaching and research, we do expect an increase in the rate of dissipation of research effort would promote stronger substitution effect in favour of teaching.

## III. Econometric Estimation of the Research Production Function

Against the backdrop of this theoretical framework, we now proceed to our econometric analysis with the following objectives in mind – (1) to test the validity of our theoretical result that research activity (fraction of time devoted to research) increases over life time and the key assumption of consumption motivation driven research in Indian academia and (2) to explore how research effort translates into different forms of knowledge outputs through the research production process.

Knowledge creation in universities can have multiple facets. New knowledge output created through academic research may either be published in peer-reviewed journals or be patented or both. Hence *publications* and *patents* are two widely used quantifiable measures of knowledge output. Further, we believe that doctoral students are integral to scientific research at universities and, therefore, the number of *PhD scholars* supervised by a faculty also constitutes an important dimension of knowledge output. We note that these three forms of knowledge outputs (PhD supervised, publications and patents) are not mutually exclusive outcomes of the process of knowledge creation at universities. We capture their interdependence in our conceptualisation of the research production function that maps research inputs into various dimensions of research output.

### *III.1 The Research Production Function: A Conceptual Framework*

The primary research input in our research production function is faculty's research effort (time devoted to research). The results of our theoretical model indicate that time devoted to research increases over faculty's professional life. In a cross-sectional analysis, this would imply that faculty members with longer academic experience would devote more time to research.

Our theoretical analysis rests on an assumption that faculty research is driven solely by consumption (as opposed to investment) motivation. Clearly, we would then expect faculty attitude towards research to act as a key determinant of her time devoted to research. To capture this attitudinal parameter, we try to understand the way she values her research as reflected in her motivation to publish. Insofar as peer recognition and/or dissemination are the primary motivations to publish, we may expect a mindset where the faculty values research *per se*, as opposed to those who are motivated to publish for pecuniary incentives like career advancement prospects. Naturally, the former mindset will significantly augment research effort, if indeed our assumption of consumption motivation driving Indian academic scientists' research is valid.

Finally, the mandate and nature of the academic institution has a role to play in determining faculty member's flexibility with regard to the time allocation problem. For instance, in institutes with large undergraduate teaching programmes, faculty would be constrained to devote a larger share of time to teaching. Likewise, we must also control for the organisational demands on faculty's time for administrative duties. Such responsibilities are not only linked to positions of academic administration (like being the Head or the Dean), but also come in various other forms like organising academic events, managing academic programmes, administering sponsored research projects and miscellaneous official correspondences.

Knowledge outcome in the form of PhD scholars is possibly directly linked to faculty's *a priori* decision to devote time to research. Higher research time should lead to larger number of PhD scholars. Moreover, senior faculty (in designation) is expected to have larger number of research scholars, not just because they have the experience and expertise to supervise research but also because students are keen to join a professor with academic stature.[11] Needles to mention, faculty engaged in sponsored research in different applied fields require large laboratory infrastructure and hence a larger research team to manage it. Therefore, faculty with more sponsored research projects is expected to supervise more research students. Moreover, as in the case of research time, we must again control for the time devoted to administrative duties. Given that large teams of PhD scholars entail managing larger laboratories and administering more sponsored projects, we may expect a positive relationship between time devoted to administrative duties and the number of PhD scholars.

In so far as publications are concerned, there is little to explain the direct effect of research time on publication record. However, one may expect non linearity in this relationship with a rising but diminishing marginal effect of research time on publications. Moreover, given that publications in science are usually co-authored with members of the laboratory team, the number of PhD students in the faculty's laboratory, although conceived as knowledge output in itself, will also act as an input in determining publication record. Among exogenous variables, the length of academic experience is expected to positively influence publication record, extending our theoretical conclusion that faculty will not only be more active but also more productive in research over the life cycle. Also, attitude towards research, as captured by her motivations to publish could affect her publication record, in the same manner as it influences research effort.

Finally, the knowledge outcome reflected in patenting activity will be directly influenced by research effort as well as the number of PhD scholars, as in the case of publications. We further argue that publication record would also directly influence faculty patenting activity. Given that Indian academia is still largely publication oriented, it is reasonable to assume that faculty would like to place all academic research outputs in the form of publications. Essentially then, the number of publications may be seen as a proxy for the entire volume of

[11] Crosta and Packman (2005) sought to address faculty productivity in terms of number of scholars supervised. The results show that, on average, a faculty member's prestige and her length of time at the institution significantly determines faculty productivity on this count.

research being conducted by faculty and only a subset of this research is patentable.[12] Therefore, we may expect publication record to positively influence patenting activity.[13]

For patenting activity, we would also like to test for the effects of a variety of exogenous factors to establish some of the less understood drivers of faculty patenting in Indian academia. There is a commonly held belief that faculty's exposure to IP driven research environments shape their patenting behaviour. We attempt to capture this exposure through various channels and posit the following hypotheses. Younger generation of faculty[14], or those trained abroad, or those with industry experience or those who engage in industrial consultancy activities may be expected to have a greater exposure to a research culture that encourage proactive technology transfer through patenting and licensing. Accordingly we may expect such faculty to engage more in patenting activity. We have already argued that patenting is still not very common in Indian academia, and is restricted to certain pockets only. In this context the institutional mandate and focus (basic sciences verses engineering/technology) are also likely to influence faculty patenting activity. Likewise, we also expect time devoted to administrative duties to positively influence patenting activity, as the process of patenting (unlike publishing) demands administrative time.

Based on the above conceptual framework we represent the research production function in a schematic diagram (figure 1), where research effort (time) and knowledge outcomes are endogenously and simultaneously determined in a recursive structure. In figure 1, we show the endogenous variables in rectangular boxes (with bold borders) on the right hand side, while specific exogenous variables are shown in ovals on the left hand side of the diagram. The dotted arrows show the pattern of interdependence among endogenous variables and the bold arrows depict the effects of exogenous variables on each of the endogenous variables.[15]

[12] Of course, this is based on the presumption that faculty can always carefully select patentable components of their research and file a provisional patent application before placing the results in the public domain to avoid any potential conflict between publications and patents. Blumenthal et al (1997) find that 19.8 percent of a sample of US academic life scientists had withheld research results for more than six months due to intellectual property rights discussions, patent applications etc.

[13] However, if there is an inherent conflict between publishing and patenting, a larger pool of publications will imply fewer patents. This possible substitution effect has been discussed in Klitkou and Gulbrandsen (2006).

[14] However, according to Audretsch and Stephan (1996) older scientists may be more willing to exploit commercial potential of their knowledge assets than their younger colleagues, who need to invest more intensively in increasing their scientific reputation within the academy.

[15] *Prima facie*, these parameters shaping faculty research behaviour are expected to be exogenously determined. However, we do not ignore the fact that some of these parameters (particularly faculty attitude and research sponsorship) could arguably be endogenously determined within the system as many of these factors do evolve over time through prolonged influences of faculty behaviour and performances. However, in a cross sectional model it is difficult to capture such evolution and hence one may justifiably use them as exogenously determined.

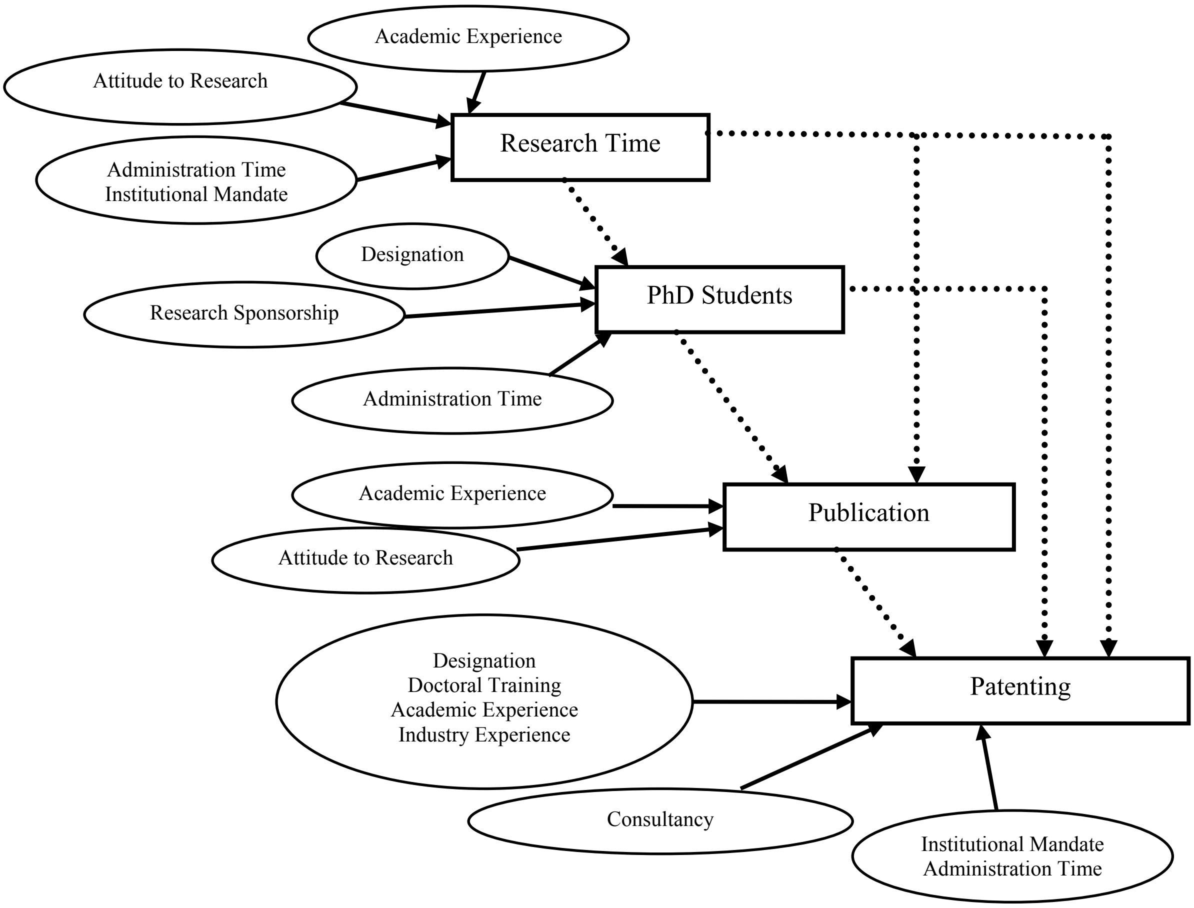


**Figure 1: The Research Production Function – A schematic framework**

### *III.2 Sample and Data*

Data for our analysis has been compiled from individual faculty level information collected through administering a questionnaire at selected academic institutions. As mentioned earlier, we selected three top tier higher educational institutes in India – Indian Institute of Science (IISC), Bangalore, Jawaharlal Nehru University (JNU), New Delhi and Indian Institute of Technology, Delhi (IITD). These institutions are considered amongst the best in India in terms of quality of faculty and students and they share significant commonalities with regard to their profile of academics, research, recruitments and student admissions, reflecting certain benchmark standards. However, unlike IISC and JNU, IITD is engaged in undergraduate teaching across disciplines. Moreover, while IISC and JNU are possibly mandated to undertake research and teaching in basic sciences, IIT Delhi has significantly greater focus on engineering and technology related fields. Therefore, we feel that there is a perceptible difference in the institutional mandate and character of IITD vis-à-vis the other two institutions. This serves our purpose of representing the top tier of Indian academia in our analysis, with adequate heterogeneity to capture institution specific effects on faculty research behaviour.

We designed a brief online questionnaire for university science faculty, containing twenty questions with multiple choice or objective/numerical responses, to obtain information on faculty background, academic activities, research profile and motivational/attitudinal parameters. The construction of our variables used in the econometric estimation is described in Appendix A. All information is self reported. From our online survey of science faculty in the three selected institutions, we obtained 92 valid and complete responses.[16] The online survey request was sent to the entire population of science faculty (around 850) in the three institutes. Although the response rate has been low (about 11%, as expected in any such surveys administered to high skilled professionals), there is no reason to expect any systematic sampling bias as the respondents emerged randomly from the population. The statistical profile of this random sample, presented in Appendix B, clearly indicate that the sample is well balanced.

### *III.3 Econometric Specification*

In order to estimate the research production function we specify a simultaneous equation model which takes the general form.

$$y_t^{'}\Gamma + x_t^{'}\mathrm{B} = u_t^{'}$$

The simultaneous equation model comprises of four structural equations in four endogenous variables (capturing *research time*, *number of research scholars*, *publication* and *patenting activity*). In our model the set of equations constitutes a fully recursive structure, where $\Gamma$ (matrix of coefficients of endogenous variables in the set of equations) is triangular. We assume the error terms ($u$'s) to be mutually uncorrelated, i.e., their variance-covariance matrix $\Sigma$ is diagonal and there are no restrictions on matrix of coefficients B.[17] In this case, the structural coefficients of the recursive model can be consistently estimated by applying classical least squares to each individual equation.[18]

We constructed the partial correlation matrix for all explanatory variables and found that none of the partial correlation coefficients are high enough to indicate any serious presence of multicollinearity that could violate the standard assumption of least square estimation (see Appendix G). To test for the presence of hetroscedasticity, we used the Cook-Weisberg (1983) test. The Cook-Weisberg test estimated the value of $\chi^2(1)$ to be 10.06, rejecting the null hypothesis of homoscedasticity for equation 1 at 1 percent level of significance. Therefore, we apply robust estimation method (weighted least squares) for equation 1 to correct for possible presence of heteroscedasticity. The dependent variable in the second equation (number of research scholars) is a non-negative count variable. We therefore use POISSON regression in this case. The last two equations representing publication rate and patenting activity, have both binary dependent variables and we apply the LOGIT model to estimate these.[19]

[16] The respondents are spread across departments of electrical engineering, civil engineering, chemical engineering, mechanical engineering and textile technology in IITD; school of physical sciences, centre for molecular medicine, school of life sciences, school of biotechnology and school of information technology in JNU; and departments of physics, instrumentation and applied physics, computer science and automation, organic chemistry, biochemistry, physical chemistry, microbiology, genetics, and departments of chemical, electrical, civil and aerospace engineering in IISC.

[17] We tested for the validity of this assumption of uncorrelated error terms across equations in our model by calculating the estimated values of $\hat{u}_1$, $\hat{u}_2$, $\hat{u}_3$, $\hat{u}_4$ to obtain the correlation matrix (see Appendix C). We find that none of the correlation coefficients are statistically significant, vindicating our assumption of mutually uncorrelated error terms across equations.

[18] *see* Wold and Jureen (1953), Klein and Su (1979), Greene (2011)

[19] Heterogeneity among individuals in terms of their innate capabilities could not be controlled in the absence of panel data, although we have controlled for individual specific attitudinal and other background factors.

The sample size of 92 may be raised as a point of concern, although we believe it is sufficiently large for estimating any econometric model with asymptotic properties. Nevertheless, since small samples *might* have large variances, we used robust (sandwich) estimate of the variance-covariance matrix of the estimators, in all equations reported in table 1. We find that the results are not any different from those obtained without robust estimation for equations 2, 3 and 4 (not reported). For equation 2, it reflects that our POISSON regression is perhaps free from the problem of over-dispersed data.[20] For the LOGIT models (equations 3 and 4), robust estimation does not provide any particular advantage – any divergence in results obtained from robust and otherwise would indicate misspecification of the model (Cameron and Trivedi, 2010). The fact that we do not find any divergence confirms that our LOGIT models do not suffer from specification problems. We have carried out additional specificity and sensitivity tests for our LOGIT models. The overall rate of correct classification is estimated to be 78.26 percent for equation 3 and 71.74 percent for equation 4. In case of equation 3 which is supposed to be predicting high rate of publications among faculty scientists, we obtain that our model correctly predicts nearly 46 percent of the instances of ‘high productivity’.

### *III.4 Results*

The results presented in table 1 vindicate our theoretical conclusion that research activity rises over faculty’s professional life time. In other words, senior faculty in terms of the length of academic experience (*yrsexpacad*) devotes more time to research (*restime*). The variable *yrsexpacad* appears with a positive and highly significant coefficient in equation 1. One could, of course, argue that junior faculty is often forced to bear a larger teaching load compared to senior faculty and hence this empirical result is far from surprising. Indeed, the partial correlation coefficient between designation and research time appears to be statistically significant although its value is only 0.26, making it difficult to come to a valid statistical conclusion. Nevertheless, in the institutions that we have covered, we did not find any obvious evidence of a systematic bias in the allocation of teaching load between senior and junior faculty – this was emphatically conveyed by the faculty members in general. To confirm this, we performed a one-way analysis of variance and concluded that there is no designation-wise variation in teaching time (Appendix D). Therefore, we construe our econometric result as a validation of our theoretical conclusion that faculty research effort increases over time. As a matter of fact, our results also reveal that senior faculty (in length of service) tend to have a higher rate of publications.

We included a quadratic term for *yrsexpacad* in the model to detect possible non-linearity in the positive relationship of academic experience (*yrsexpacad*) with research time (*restime*) and publications (*pub*). While we failed to detect any non-linearity in the relationship between academic experience and publications, the coefficient of the quadratic term for *yrsexpacad* in our estimated equation for research time appeared negative and significant, suggesting that experience augments research effort at a declining rate. The maximum research time is reached at the 25$^{th}$ year in service and it falls marginally thereafter. It is a small tail of older faculty (20% in our sample, supposedly with an average age of 55+) who

[20] We confirmed this by a test of over-dispersion a la Cameron and Trivedi (2010). The test is performed by estimating an auxiliary regression of a generated dependent variable, $\{(y-\hat{\mu})^2 - y\}/\hat{\mu}$ on $\hat{\mu}$, without an intercept term: $(\{(y-\hat{\mu})^2 - y\}/\hat{\mu})_i = 0.37\ \hat{\mu}_i + u_i$ with the s.e. of the coefficient of $\hat{\mu}$ being 0.385 implying that it is not statistically significant. Hence we do not detect any over-dispersion.

are on a downward path for their share of research time.[21] These older faculty, who have seen the rapid progress of science over more than 25 years of their professional career, would perhaps better appreciate the rate of depreciation of knowledge than their younger energetic counterparts and would accordingly assign a value of $\delta$ considerably higher than their younger colleagues. In that case, the tapering off of research time after 25 years of service seems perfectly consistent with our theoretical proposition (4). Indeed, this non-linearity in the relationship between academic experience and research effort, by no means, violates the spirit of our theoretical proposition (1).

We conclude that Indian academic scientists, *ceteris paribus*, tend to become not only more active but also more productive in research over their lifetime. In other words, (academic) experience does augment knowledge creation through greater research effort and higher publication rate. One may, of course, argue that our higher publication rates of experienced senior faculty may be attributed to the fact that they tend to attract more and more funding over time and hence more research students and thus becoming more productive over the life cycle. This is what we have hypothesised for our second regression model and the results vindicate this position. Senior faculty (in designation) and faculty with a larger portfolio of sponsored research do tend to have a larger team of PhD scholars. This would then undermine the role of experience per se in raising research productivity over life time.

Moreover, our results also confirm that faculty who values research *per se* (as opposed to valuing research for its pecuniary incentives) (*resvalue*) not only devote more time to research (*restime*), but also publishes more (*pub*). This validates our core assumption underlying the theoretical model that it is the consumption (as distinct from the investment) motivation that is the prime driving force for academic research in India.

[21] One may interpret this result as a reflection of the presence of some investment motivation for research purely in terms of personal career advancement gains – most academics are expected to continue to aim for promotion until their early 50s and then to admit to themselves that they are unlikely to go further after they reach 55. Preliminary results in Turner and Mairesse (2003) suggest that French physicists are more productive every year until they turn 52 but at a diminishing rate. However, this is not a consideration in the Indian academia, as all faculty appointments are confirmed (tenured) within one year. Moreover, it normally takes 16 years to become a full professor in Indian academia at a mean age of 46 years. The tapering off that we detect at the age of 55 is therefore unlikely to be linked to becoming a full professor. Moreover, our econometric results reported below suggest a strong presence of consumption motivation. Indeed, we have a different explanation to offer for this result that is consistent with our theoretical construct.

***Table I: Structural Estimation of the Recursive Simultaneous Equation System***

| | *Equation 1* **restime** (GLS) | *Equation 2* **phdstdnts** (POISSON) | *Equation 3* **pub** (LOGIT) | *Equation 4* **pat** (LOGIT) |
|---|---|---|---|---|
| ***restime*** | | 0.011** | 0.443** | 0.079*** |
| | | (0.005) | (0.224) | (0.027) |
| ***restime***$^2$ | | | -0.003* | |
| | | | (0.002) | |
| ***phdstdnts*** | | | 0.251** | 0.193** |
| | | | (0.116) | (0.100) |
| ***pub*** | | | | -0.205 |
| | | | | (0.624) |
| ***desig*** | | -0.161** | | |
| | | (0.082) | | |
| ***foreignphd*** | | | | 0.261 |
| | | | | (0.555) |
| ***yrsexpacad*** | 1.363*** | | 0.079** | -0.037 |
| | (0.435) | | (0.035) | (0.027) |
| ***yrsexpacad***$^2$ | -0.027** | | | |
| | (0.013) | | | |
| ***yrsexpind*** | | | | 0.160 |
| | | | | (0.124) |
| ***resvalue*** | 5.762** | | 2.543** | |
| | (2.679) | | (1.026) | |
| ***resspons*** | | 0.005** | | |
| | | (0.002) | | |
| ***consultancy*** | | | | 0.007 |
| | | | | (0.548) |
| ***IITD*** | -9.754*** | | | 1.373** |
| | (2.703) | | | (0.666) |
| ***admintime*** | -0.807*** | 0.014** | | 0.077** |
| (CTRL) | (0.114) | (0.006) | | (0.034) |
| ***cons*** | 54.869*** | 0.688 | -20.694*** | -6.846*** |
| | (3.965) | (0.498) | (7.862) | (1.929) |
| F/ $\chi^2$ | 15.94*** | 28.68*** | 19.15** | 18.63** |
| No. of obsv. | 92 | 92 | 92 | 92 |

*Note: The robust standard errors are given in parenthesis*
**significant at 10% level; ** at 5% level; *** at 1% level*

The results largely establish the postulated recursive structure of the research production function. Research time (*restime*) significantly affects all knowledge outcome variables (*phdstdnts*, *pub*, *pat*).[22] The number of PhD scholars (*phdstdnts*) has a positive and significant effect on both publications (*pub*) and patenting (*pat*). However, publications do not appear to have any significant impact on patenting. We thus fail to find any evidence of

[22] In order to detect possible non-linearity in the positive impact of research time on research outputs, we included a quadratic term in the estimated equation for PhD scholars, publications and patenting. As hypothesised, the quadratic term appears negative (and marginally significant) only in the equation for publications confirming a rising (with a slight tapering off effect) of research time on publications.

either a complementarity between publication and patenting activities or a conflict between them.[23]

As expected, institutional mandate matters. Faculty at IITD that has a strong undergraduate teaching programme tend to get less time for research. At the same time they appear to be more active in patenting, given the institutional mandate and focus on engineering/technology at IITD as opposed to basic science in the two other institutions (IISC and JNU).

With regard to patenting activity, we highlight some of the interesting conclusions emerging from our econometric model. Although, we have established, theoretically and econometrically, that faculty with longer experience are more active in research (both in terms of research effort and publications), there is no evidence to confirm that they are also more active in patenting compared to their less experienced counterparts – *yrsexpacad* does not appear statistically significant in the equation for *pat*.[24] To put it differently, less experienced faculty may have a lower research drive relative to seniors, but they are not less active when it comes to patenting. We wonder whether this is a reflection of a slowly changing research approach of the Indian academia towards a more IP driven path. Secondly, we fail to find any evidence to suggest that faculty's exposure to IP oriented research culture augments patenting activity. None of the channels of this exposure that we incorporated, namely younger generation (*yrsexpacad*), training abroad (*foreignphd*), industry experience (*yrsexpind*), consultancy activities (*consultancy*), appeared with a significant coefficient in the estimated equation.

Consistent with our *a-priori* hypotheses, the control variable of time for administrative duties (*admintime*) appears to have a dampening effect on research time (*restime*) but boosts PhD scholars (*phdstdnts*) and patenting activity (*pat*) as both of these outcomes involve administrative functions.

## IV. CONCLUDING REMARKS

We have established in this paper that Indian academic scientists, *ceteris paribus*, tend to become not only more active but also more productive in research over their lifetime.

Our theoretical result is driven by the assumption that it is the consumption motivation that drives science research by university faculty in India, and not the investment motivation. Apart from anecdotal justification, our econometric analysis confirms the validity of this assumption.

Our econometric results also establish a recursive structure in which research effort drives various forms of knowledge outcomes, namely PhD scholars, publications and patents, in a *sequential* manner. We also dispel some of the commonly held beliefs regarding patenting behaviour of academic scientists. For instance, we find that exposure to an IP oriented research culture does not augment patenting activity.

[23] It may be noted that there may some of the variables like research time or PhD students are likely to influence publication or patent only with a time lag. Some cross sectional studies have captured such dynamic effects using past information (Blundell et al. (2002), Hottenrott and Thorwarth (2011), Hottenrott and Lawson (2013)). However, this was not feasible in the context of the present study where all information is self reported and pertains to the time of reporting. In the absence of any violent fluctuations in the time trend of these variables, this is unlikely to matter much in capturing the underlying relationships.

[24] Interestingly, Azoulay et al (2007), from a large sample of 3862 scientists, concluded that mid-career academics are more likely to patent than their younger or older colleagues.

All these have serious policy implications. The recently renewed policy interest in strengthening research and knowledge creation in Indian academia has revealed itself in the form of top down policy directives, essentially revolving around an IP driven approach.[25] However, insofar as this policy approach creates an IP driven attitude towards research among Indian academic scientists, this will definitely not help to augment research and knowledge creation in any way. After all, we show that exposure to IP culture has not enthused Indian academic scientists to become more active in patenting.

Moreover, in a sequential structure, patenting comes at the last step of knowledge creation. Therefore, a policy approach exclusively centred on IP, ignoring the crucial initial steps of knowledge creation (research effort, PhD scholars and publications), could prove to be rather ineffective. As a matter of fact, our results seem to suggest that such a policy approach could even potentially be counter-productive, as it may actually dampen the key driver of knowledge creation in Indian academia by undermining the importance of the *consumption motivation* for research.

Ideally, a policy regime must emphasise on research excellence through increased publications in the first place and should not dilute the importance of teaching and research guidance. Institutionalising IPRs can only be considered as an important supplementary policy instrument rather than a stand-alone policy framework to energise science research and knowledge creation in Indian universities.

[25] In the interim, a bill (The Protection and Utilisation of Public Funded Intellectual Property Bill 2008), inspired by the U.S. Bayh-Dole Act of 1980, was introduced in the Indian Parliament to stimulate public-funded research for greater industrial application, which is yet to be enacted.

# <u>APPENDIX A: VARIABLES</u>

<u>Endogenous variables</u>
*Research Time*: We construct a variable ***restime*** by adding the share of faculty's time devoted to research and research supervision as well as to consultancy wherever applicable (see footnote 3).
*Number of Research Scholars*: We consider a variable called ***phdstdnts*** which is the number of PhD scholars under the supervision of the particular faculty at the time of survey.
*Publication*: Publication record is a standard yardstick of faculty performance. Although there are two dimensions of publication record – quantity and quality, it is always difficult to get an objective measure of quality. Acknowledging this limitation, we only look at the number of publications of a faculty (with no reference to the quality) to capture her publication record. We look at the current rate of publication averaged over the last three years. During our pilot survey, we observed reluctance of respondents to divulge the actual number. Hence the questionnaire was designed to include two response categories of publication rate. Based on the responses we construct a binary variable ***pub*** which takes the value 1 (one) if annual publication rate (average over preceding three years) is high (> 3) and 0 (zero) otherwise.
*Patenting Activity*: Given that in our sample only a few faculty have obtained patents, while a number of them have started applying for patents, we felt that patenting activity of faculty may be best captured by looking at both patent applications as well as patents granted. We give due importance to patent applications since our primary objective is to model inclination towards patenting in the first place. We collected data on the number of patent applications and the number of patents granted. We construct a binary variable ***pat*** to represent patenting activity of a faculty, which takes the value 0 (zero) if the faculty has a zero response to the number of patents applied as well as to number of patents granted, and 1 (one) otherwise.

<u>Exogenous variables</u>
*Years of Experience*: To capture professional experience of a faculty, we construct two variables – number of years in academics (***yrsexpacad***) and number of years in industry (***yrsexpind***).
*Designation*: We construct a variable ***desig*** that takes the value 1 if faculty reports her designation as professor, 2 for associate professor and 3 for assistant professor.
*Doctoral Training*: We create a binary variable called ***foreignphd*** and assign it value 1 (one) if a particular faculty has a doctoral degree from abroad and 0 (zero) otherwise.
*Attitude towards Research*: We believe that faculty's motivation to publish could approximately reflect how they value research. If indeed faculty motivation to publish is essentially driven by considerations of academic (peer) recognition and wider dissemination of research results. These would reflect faculty's intrinsic valuation of research pursuits that goes beyond considerations of extrinsic motivations of career advancement. On these motivational aspects, faculty was asked to separately indicate the level of importance on a six point scale (0: for least importance and 5: for highest importance). We devised a composite measure of the two motivational factors (peer recognition and dissemination) by adding scores on each of these components for every respondent. We created a binary variable called ***resvalue*** and assigned it value 1 (one) if the sum of the corresponding scores was more than 5 indicating that faculty *per se* has a high intrinsic valuation of research and 0 (zero) otherwise.
*Research sponsorship*: We construct a variable ***resspons*** reflecting the percentage share of total research (as reported by the respondent) that is externally sponsored.
*Institutional Mandate*: To capture the role of institutional mandate we create a dummy ***IITD*** (which takes the value 1 when faculty belongs to IITD and 0 otherwise), as explained earlier.
*Administration Time*: We construct a variable ***admintime*** as the share of total time devoted to administrative duties assigned to the respondent.
*Consultancy*: We construct a dummy ***consultancy*** that takes the value 1 if faculty reports consultancy activities, else 0.

## APPENDIX B: THE SAMPLE PROFILE

Sample size (Number of Faculty): 92 (JNU = 25, IITD = 24, IISC = 43)
Research time: Mean = 57.01, s.d. = 14.51, Min: 30, Max: 90, *skewness*: 0.273, *kurtosis*: 2.806, SK test for normality confirms that this variable is normally distributed.
PhD Scholars: Mean = 4.96; Min: 0, Max: 12.
Publication rate: High (> 3) = 24; Low (≤ 3) = 68.
Patenting: Active = 40; Not active = 52.
Designation: Professor = 49, Associate Professor = 22, Assistant Professor = 21
Training: PhD from abroad = 30; PhD from India = 62
Academic experience: Mean= 15.22 years, s.d. = 9.47, Min: 1, Max: 37.
Sponsored res. (share): Mean = 60.98, s.d. = 34.72; (Min: 0, Max: 100).

## APPENDIX C: CORRELATION MATRIX OF ESTIMATED ERRORS

| | $\hat{u}_1$ | $\hat{u}_2$ | $\hat{u}_3$ | $\hat{u}_4$ |
|---|---|---|---|---|
| $\hat{u}_1$ | 1.0000 | | | |
| $\hat{u}_2$ | 0.0010<br>0.9924 | 1.0000 | | |
| $\hat{u}_3$ | 0.1126<br>0.2853 | 0.0808<br>0.4438 | 1.0000 | |
| $\hat{u}_4$ | -0.0119<br>0.9103 | 0.0324<br>0.7591 | 0.0428<br>0.6851 | 1.0000 |

*Note: The p- values are given in italics*

## APPENDIX D: ONE WAY ANALYSIS OF VARIANCE FOR TEACHING TIME BY DESIGNATION CATEGORIES

| | SS | df | MS |
|---|---|---|---|
| Between groups | 2029.52521 | 2 | 1014.76261 |
| Within groups | 12306.9422 | 89 | 138.280249 |
| Total | 14336.4674 | 91 | 157.543598 |

Bartlett's test for equal variances: chi2(2) = 1.0292 Prob>chi2 = 0.598

# APPENDIX G: PARTIAL CORRELATION MATRIX OF VARIABLES

| | ***restime*** | ***phdstdnts*** | ***pub*** | ***pat*** | ***Yrsexpacad*** | ***yrsexpind*** | ***desig*** | ***foreignphd*** | ***resvalue*** | ***resspons*** | ***admintime*** | ***Consultancy*** | ***IITD*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***restime*** | 1.0000 | | | | | | | | | | | | |
| ***phdstdnts*** | 0.1888 | 1.0000 | | | | | | | | | | | |
| | *0.0716* | | | | | | | | | | | | |
| ***pub*** | 0.3048 | 0.2832 | 1.0000 | | | | | | | | | | |
| | *0.0031* | *0.0062* | | | | | | | | | | | |
| ***pat*** | 0.1816 | 0.2876 | 0.0782 | 1.0000 | | | | | | | | | |
| | *0.0831* | *0.0054* | *0.4590* | | | | | | | | | | |
| ***yrsexpacad*** | 0.3383 | 0.1773 | 0.1778 | 0.0188 | 1.0000 | | | | | | | | |
| | *0.0010* | *0.0909* | *0.0900* | *0.8586* | | | | | | | | | |
| ***yrsexpind*** | -0.1300 | 0.0151 | -0.0052 | 0.1424 | -0.1785 | 1.0000 | | | | | | | |
| | *0.2169* | *0.8863* | *0.9610* | *0.1756* | *0.0887* | | | | | | | | |
| ***desig*** | -0.2604 | -0.2859 | -0.1725 | -0.2099 | -0.7655 | 0.0429 | 1.0000 | | | | | | |
| | *0.0122* | *0.0057* | *0.1002* | *0.0446* | *0.0000* | *0.6844* | | | | | | | |
| ***foreignphd*** | -0.0728 | -0.1548 | -0.2020 | 0.0447 | -0.0878 | -0.0542 | -0.0530 | 1.0000 | | | | | |
| | *0.4903* | *0.1407* | *0.0534* | *0.6719* | *0.4050* | *0.6080* | *0.6156* | | | | | | |
| ***resvalue*** | 0.1229 | 0.1349 | 0.2742 | 0.1319 | -0.1824 | -0.1208 | -0.0355 | 0.1428 | 1.0000 | | | | |
| | *0.2433* | *0.1999* | *0.0082* | *0.2101* | *0.0818* | *0.2512* | *0.7366* | *0.1745* | | | | | |
| ***resspons*** | -0.0738 | 0.3022 | 0.0943 | 0.0799 | -0.1519 | -0.0486 | 0.1126 | -0.2010 | 0.0978 | 1.0000 | | | |
| | *0.4842* | *0.0034* | *0.3714* | *0.4489* | *0.1484* | *0.6458* | *0.2853* | *0.0547* | *0.3539* | | | | |
| ***admintime*** | -0.5366 | 0.1974 | 0.0317 | 0.1137 | 0.0092 | 0.1577 | -0.0776 | 0.0333 | 0.0746 | 0.3245 | 1.0000 | | |
| | *0.0000* | *0.0593* | *0.7641* | *0.2803* | *0.9306* | *0.1333* | *0.4623* | *0.7529* | *0.4798* | *0.0016* | | | |
| ***Consultancy*** | 0.2910 | 0.3066 | 0.2338 | 0.1953 | 0.1087 | 0.1536 | -0.2191 | -0.1301 | 0.1255 | -0.0227 | -0.0793 | 1.0000 | |
| | *0.0049* | *0.0029* | *0.0249* | *0.0620* | *0.3023* | *0.1439* | *0.0358* | *0.2163* | *0.2334* | *0.8298* | *0.4522* | | |
| ***IITD*** | -0.2714 | -0.1322 | -0.2402 | 0.0782 | -0.0981 | -0.0376 | -0.0211 | 0.1676 | -0.1064 | -0.2104 | -0.0887 | 0.0816 | 1.0000 |
| | *0.0089* | *0.2091* | *0.0211* | *0.4590* | *0.3520* | *0.7218* | *0.8420* | *0.1103* | *0.3129* | *0.0441* | *0.4005* | *0.4394* | |

*Note: The p-values are given in italics*

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