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Human capital and higher education: rate of returns across disciplines

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Abstract

This study attempts to examine the returns across various levels and majors in higher education using nationally representative India Human Development Survey (IHDS) data 2011-2012. Higher education here is taken as a heterogeneous sector with various majors each having varying demand in the labour market owing to skill differences. The existing literature on returns to higher education in India fails to assess the probable heterogeneity of returns to higher education across various majors. The present analysis draws on extended Mincerian earnings function to estimate the wage returns to different professional and non-professional degrees with varying majors. After correcting for selectivity bias following Heckman's two-step selectivity correction procedure, the results show highest returns for medical graduates followed by engineering graduates and professional postgraduates.

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1. Introduction

Human capital has long been accepted as crucial for economic growth (see, for example, Schultz 1961; Becker 1994) by way of increasing real earnings per worker (Schultz 1961, 1) thereby reducing poverty (see, for example, Bloom, Canning, and Chan 2006) and increasing economic output in both developed and developing economies (see, for example, Barro and Lee 2013). Education is one of the major components of human capital and the rate of returns to education determines the amount spent on education by the household both for boys and girls (see, Kambhampati 2008, 3).

In rural India, the average share of household expenditure on higher education in 2014 was 15.3 per cent and in urban it is 18.4 per cent of total household expenditure (see, Chandrasekhar 2016, 9). Besides, there is a general increase in demand for technical education as compared to general education, especially in the post-liberalisation period due to the lucrative labour market outcomes of vocational and technical education (see, for example, Duraisamy and Duraisamy 1993). Furthermore, the rising skill premia of higher educated individuals has contributed significantly to the increasing inequality in wage distribution and, hence, income inequality (see, for example, Lemieux 2006; Kijima 2006).

The existing literature on returns to education in India (see, for example, Tilak 1987; Duraisamy 2002; Agrawal 2012; Rani 2014), estimates the returns by levels of education, like primary, secondary, and higher education and fails to assess the probable heterogeneity of returns to higher education across various majors (/disciplines). Higher education is treated as a homogeneous entity and the resulting returns are generally averages across education levels, income quantiles and labour market sectors. Higher education is a heterogeneous sector with varying subjects or majors broadly divided into technical and non-technical education and may have varying returns for each[1]. Evidence from international literature reveals varying returns for different majors in higher education (see, for example, Weiss 1971). Moreover, these majors have varying demand in the labour market owing to skill biased technological changes (Kijima 2006). An analysis of the returns to various majors in higher education would give a clearer picture of the concentration of skill premium owing to skill biased technological change and better explain the inequality in wage distribution.

Therefore, this study attempts to assess the distribution of returns across a few majors and by levels in higher education using nationally representative India Human Development Survey data 2011-12. The returns to education are calculated, particularly, for medicine and engineering majors among professional graduate degrees. Further, returns by level of education are calculated for non-professional graduate degree, non-professional postgraduate and higher degrees and for

[1] Higher education is broadly divided into general/non-professional and technical/professional education. It includes graduate and above degree in different majors, and graduate and above diploma and certificate course in various vocational majors. At the graduate level, Bachelor of Art (BA), Bachelor of Science (BSc), and Bachelor of Commerce (B. Com) come under non-professional education; Bachelor of Medicine (MBBS), Bachelor of Engineering (BE), Bachelor of Technology (BTech), Bachelor of computer application (BCA), Bachelor of Business Administration (BBA), Bachelor of Law (LLB), Bachelor of Pharmacy (BPharm) and similar professional courses come under professional education. All these professional and non-professional degrees have their corresponding postgraduate and higher degrees.

professional postgraduate degrees. Additionally, the returns for vocational diploma are also calculated. The present analysis draws on extended Mincerian earnings function to estimate the returns to majors and levels in higher education. The results show highest wage returns for medical graduates followed by engineering graduates.

The rest of the paper is organised as follows: section two briefly outlines the relevant literature; section three elaborates on the empirical specification; section four describes data and descriptive statistics; section five explains the results; and section six concludes the study.

2. Empirical literature

Conventional rate of returns analysis shows higher education in a less favorable light with lower returns than primary and secondary schooling. Returns to higher education was estimated to be 10.8 percent whereas it was 18.9 percent for primary and secondary education as revealed from the country level studies of 98 countries from 1960 to 1997 (Psacharopoulos and Patrinos 2004, 114-115). In India, the returns to education were found to increase up to secondary level and decline thereafter (Duraisamy 2002, 614). However, the trend in returns from 1983 to 1993 varied across gender with the returns to women's primary and middle levels of education declining while those to secondary and college levels increasing during the decade (Duraisamy 2002, 619).

More recent studies show that returns to education increase with the level of education and is heterogeneous across location, caste and religion (see, for example, Subbaraman and Von Witzke 2006; Agrawal 2012; Rani 2014), income quantiles (see, for example, Azam 2012), English language ability (see, for example, Rani 2014; Azam, Chin, and Prakash 2013) and cognitive and non-cognitive skills (see, for example, Heckman, Humphries, and Veramendi 2016). Refuting the results of Duraisamy (2002), Rani (2014) finds that returns to higher education vary at a great deal ranging between 4.9% among the rural workers and 38.2% among fluent English ability group. Conversely, returns to English language skills increases with higher education and experience (see, for example, Azam, Chin, and Prakash 2013).

The returns to higher education when disaggregated across quantiles reveal heterogeneity favouring the top quantiles (Azam 2012, 1145; see, also, Agrawal 2012). The trend in returns to education measured by the price paid to workers from 1983 to 1993, is positive and uniform across all levels of education whereas from 1993 to 2004 the increase in prices paid is not only much higher for tertiary and secondary education but also heterogeneous across income classes.

Moreover, in the segmented labour market of India, casual and regular workers have varied returns to education and experience, where casual workers face flat returns and regular workers have positive and rising returns with education levels (see, for example, Dutta 2006). Besides, lower caste casual workers are discriminated in the labour market, earning lower wages, whereas lower caste regular workers earn better wages than individuals from other castes (Subbaraman and Von Witzke 2006, 7). This is more so for female casual workers who find no additional advantage for secondary or graduate level of education in terms of wage earnings (Vatta, Sato, and Taneja 2016, 128).

The varying returns to higher education points to the inequality increasing effect of higher education on wages (see, also, Lemieux 2006) mainly attributed to skill premium resulting from rising demand for skilled labour as a consequence of skilled biased technological change (see, Kijima 2006, 110)) and skill upgrading within industries (Chamarbagwala 2006). Interestingly, this wage inequality is concentrated in the top end of the wage distribution (see, for example, Lemieux 2006; Azam 2012).

Additionally, education has both market and non-market returns. Heckman et al. (2016) finds that both cognitive and non-cognitive endowments affect schooling choices and outcomes. High-ability individuals are found to have substantial continuation value components of graduating high school and completing college as compared to low-ability individuals who have substantial direct effects of graduating high school, but little continuation value. This apart, the study finds evidence of sorting gains at higher levels of schooling for wage outcomes, supporting the arguments of Becker (1994) that schooling has strong causal effects on market and non-market outcomes.

3. Empirical Specification

Returns to education are generally estimated by using Mincer's "basic" earnings function method (Mincer 1974) and "extended" earnings function is used to estimate the returns to education at different levels or even different types of curriculum. The basic wage equation is estimated by regressing the log weekly wage on a set of human capital variables like years of schooling and experience and its square. This basic OLS estimation amounts to biased results due to unobserved individual and family characteristics like ability and family background, respectively. If ability and education attainment are correlated, then the estimated returns could be biased. A more able person may more effectively convert schooling attainments into human capital and earn higher returns to education. On the other hand, if learning ability is positively correlated with earning ability, then the returns to education will be reduced (underestimated). Also, measurement errors could also result in biased estimates of returns to education.

Likewise, family characteristics like family income and status may influence the education attainment of an individual. Parental education has positive impact on the individual's higher education participation decisions (see, for example, Basant and Sen 2014) and schooling outcomes (see, for example, Card 1999). Parental education coupled with higher income and better social status may offer better access to education and employment opportunities to their wards through better networking and communication and may receive better returns (see, for example, Krishnan 2009; Siphambe 2000). Moreover, market in higher education being characterized by market imperfections (see, for example, Chattopadhyay 2012) the existence of information asymmetry may result in varying marginal cost of education for different individuals, adversely affecting the poorer families with higher cost of education (Checchi 2006, pp. 202-203).

The present analysis draws on the "extended" earnings function method to estimate the returns to higher education by different majors – medical and engineering, and by different levels – graduate, postgraduate and above, postgraduate professional degrees and vocational diploma. The extended earnings function is specified as below:

$$lnw = \alpha + \beta H_i + \beta_1 D_i + \beta_2 O_i + \beta_3 L_i + \varepsilon_i \quad (1)$$

Where lnw is the logarithm of hourly wage, H_i represents human capital dummy for individual i representing a major or a degree in higher education; D_i denotes demographic characteristics of individual i; O_i represents dummies for employment type and occupation division of individual i; L_i is location dummy of individual i (regional and state); and ε_i represents the unobserved characteristics of individual i that may influence the wage rate. The variables age and age square stand proxy for experience and experience square (see, also, Kingdon and Theopold 2008; Madheswaran and Attewell 2007) as it is expected that experience increases return but at diminishing rate.

The above wage equation (1) suffers from selectivity bias arising out of self-selection of sample. Here the wage rate is estimated for a sample of educated and employed individuals, amounting to self-selection. This sample may not be representative as it leaves out the entire educated unemployed in the labour market. The selectivity issue here is that those unemployed are not in the work force because their reservation wage is higher than actual wage and the OLS estimation of wage would be biased, if not corrected for selectivity. To account for selectivity issue Heckman's two step procedure (see, Heckman 1979) is applied. In the first stage the probability to have worked is estimated through a participation (selection) equation (2). Here, non-labour income of the individual and household size is used as the identifying variables (see, for example, Rani 2014; Agrawal 2012) to mark the exclusion restriction which can affect the selection equation but can be excluded from earnings equation. The non-labour income includes all other incomes except wage and salary[2].

The first stage probit model to estimate the participation equation is specified as follows:

$$y_i = x_i\varphi + \mu_i \qquad (2)$$

Where y_i takes the value one if individual i participates in work for a wage and zero otherwise; x represents human capital variables, demographic variables and the identifying variables; and μ is the error term [$\mu \sim N(0, \sigma_\mu^2)$]. With the estimates of participation equation an inverse mills ratio is created. The inverse Mills ratio is the ratio of the probability density function to the cumulative distribution function of a distribution ($\lambda = \frac{\emptyset(x_i\varphi)}{\omega(x_i\varphi)}$). The inverse Mills ratio is the selection variable λ to be used as an additional control variable in the earnings equation.

In the second stage, the augmented Mincerian earnings function for hourly wage is estimated, using ordinary least square (OLS), for individual i holding a higher education degree. The equation (2) which includes a series of dummy variables, referring to different majors and levels in higher education, in lieu of schooling variable$s$, is further extended by incorporating the Mills ratio (selection variable λ), obtained from the estimates of participation equation, as an additional regressor in the second stage.

$$lnw = \alpha + \beta H_i + \beta_1 D_i + \beta_2 O_i + \beta_4 L_i + \theta\lambda + \varepsilon_i \qquad (3)$$

where θ is the coefficient of selection variable λ. The sample for the wage equation consists of wage workers alone and, therefore, the wage rate is estimated for the uncensored observation. The equation is estimated with two model specifications: first, using gender as an explanatory dummy variable and second, using gender as an interaction variable, interacting human capital variables with gender, in order to examine the gendered differences in wage returns to higher education.

[2] Non-labour income includes Income from property, pensions, renting of property, interest, dividends, Government pensions, private pensions, sale of non-agricultural land, sale of agricultural land, and other government sources.

Since locational characteristics have differential influence on wages of workers, the model is run, separately, for rural and urban sectors, in both specifications.

4. Data and Descriptive Statistics

The study draws on the data from the nationally representative India Human Development Survey-II (IHDS-II) 2012, jointly conducted by the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi. The IHDS-II covers all states and union territories of India with the exception of Andaman/Nicobar and Lakshadweep. The survey covers 42,152 households in 384 districts, 1420 villages and 1042 urban blocks located in 276 towns and cities across India. The villages and urban blocks are the primary sampling unit (PSU) from which the rural sample was drawn using stratified random sampling and the urban sample from a stratified sample of towns and cities within states (or groups of states) selected by probability proportional to population (PPP) (Desai and Vanneman 2015).

The data provides information on demographic characteristics of households like household residence (rural/urban), household size, social groups category (Brahmins, forward castes, other backward castes (OBC), Dalits, Adivasis) and religion (Hindu, Muslim, Christian, Sikh, Buddhist, Jain)[3]. The data also details about the principal source of income for the household which may include farm income, income from interests (or dividend or capital gains), property, pension, income from other sources. Details of individual characteristics like age, gender, education, marital status and relationship to the head of the household are also provided. The data also informs about the occupation, industry, hours of work in a usual day and wages and salaries of individuals.

4.1 Variables description

The outcome variable is logarithm of hourly wage of individuals with a higher education degree. The independent variables are broadly categorised into human capital variables, demographic variables and occupational variables. The human capital variables are the variables of interest in this analysis and demographic and occupational variables are additional control variables.

The focus of this analysis is on human capital variables consisting of various degrees and majors in higher education. Higher education variables include graduate degree in non-professional education (BA, BSc, B. Com, etc.); graduate degree in engineering (BE, B. Tech.); graduate degree in medicine (MBBS/BAMS); post-graduate and higher degree in non-professional education (Masters, Ph.D.); post-graduate degree in professional education (MD, Law, MBA, CA etc.); and diploma in vocational education (Diploma <3 years; Diploma 3+ years). The reference category is non-graduates (higher secondary or graduation not completed)[4].

The demographic variables include age, age square (proxy for experience); gender; socio-religious category [Brahmins (reference category), forward castes, other backward castes (OBC), Dalits (Scheduled Castes), Adivasis (Scheduled Tribes), Muslims and other minority religions (Christians, Sikhs, Buddhists, Jains)]; number of dependents both males and females below 12

[3]An Indian household may have both religious identity and caste identity as well.

[4] Non-graduates include those who have passed higher secondary education consisting of twelve years of schooling; and those not completed graduation.

years and above 65 years as a control for dependency; and marital status (unmarried as the reference category).

Occupation variables consist of various type of occupation divisions and employment status. According to National Classification of Occupations (NCO) 1968, there are nine divisions of occupations like professional, technical and related workers – division one; administrative, executive & managerial workers – division two; clerical & related workers – division three; sales workers – division four; service workers – division five; farmers, fishermen, hunters, loggers & related workers – division six; production and related workers – division seven; transport equipment operators – division eight; laborer – division nine; and unclassified workers. The employment status here refers to regular and casual work.

The locational variables are state dummies[5] to control for state fixed effect; and regional characteristics is accounted for by rural and urban samples, separately.

Table I Descriptive Statistics of Variables

	Rural		Urban	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Log Hourly wage	3.255	0.873	3.820	0.871
Hourly wage	38.681	42.874	64.564	61.259
Age	33.304	10.505	36.822	11.180
Age square	1219.463	800.171	1480.851	895.459
Non-graduates	0.570	0.495	0.387	0.487
Non-professional Graduates	0.276	0.447	0.378	0.485
Engineering Graduates	0.007	0.085	0.022	0.146
Medical Graduates	0.003	0.057	0.008	0.089
Non-professional Postgraduate & above	0.117	0.321	0.138	0.345
Professional Postgraduates	0.009	0.093	0.034	0.181
Vocational Diploma <3 years	0.013	0.111	0.023	0.151
Vocational Diploma 3+ years	0.002	0.044	0.008	0.087
Other	0.003	0.057	0.002	0.047
Gender	0.180	0.384	0.210	0.407
Brahmin	0.069	0.254	0.117	0.321
Forward caste	0.182	0.386	0.292	0.455
OBC	0.328	0.470	0.297	0.457
Dalit	0.228	0.420	0.144	0.351
Adivasi	0.092	0.289	0.035	0.183
Muslim	0.068	0.252	0.068	0.252
Christian, Sikh, Jain	0.032	0.177	0.047	0.212
Married	0.666	0.472	0.687	0.464
No. of male children	0.678	0.872	0.510	0.736
No. of female children	0.632	0.899	0.460	0.725
No. of senior citizens male	0.282	0.466	0.247	0.439
No. of senior citizens female	0.275	0.457	0.256	0.452
Casual work	0.565	0.496	0.314	0.464

[5] The results of the state dummies are not presented for the sake of brevity.

Professional, technical and related workers	0.296	0.456	0.314	0.464
Administrative, Executive & Managerial Workers	0.021	0.143	0.068	0.252
Clerical & Related Workers	0.122	0.327	0.265	0.441
Sales Workers	0.046	0.209	0.090	0.286
Service Workers	0.042	0.200	0.052	0.222
Farmers, Fishermen, Hunters, Loggers & Related Workers	0.156	0.363	0.011	0.105
Production & Related Workers	0.033	0.178	0.033	0.180
Transport Equipment Operators	0.062	0.242	0.079	0.270
Labourers	0.219	0.414	0.077	0.267
Unclassified	0.004	0.065	0.010	0.099
Number of observations	3,485		4,876	

Source: Author's computation

5. Empirical Results

The above extended Mincerian wage equation (equation 3), after selectivity correction, is estimated using ordinary least square method where the natural logarithm of hourly wages of individuals is a function of demographic, human capital and occupation variables. The wage estimates for the full sample i.e., rural and urban combined, without and with interaction variables are given in Table (2), columns (1) and (2), respectively. The estimates for rural sample is given in columns (3) and (4) and for urban sample in columns (5) and (6), respectively. The Mills ratio (the lambda in table 2) is positive and significant indicating that the correlation coefficient of the error terms of the participation equation and wage equation are significant. Meaning, the wages of the non-random sample is upward biased compared to the random sample. The results are robust and the high and significant value of Wald chi2 test shows that the model is better fit for both rural and urban sample, where all the statistically significant predicator variables leads to better predication.

The variable of interest in this analysis is the human capital variable denoted by non-professional graduate, engineering graduates, medical graduates, non-professional postgraduates, professional graduates and vocational diploma. The reference category is non-graduates. The wage estimates are all positive and significant except in the case of medical graduates and professional postgraduates and vocational diploma (3+ years) in the rural sample. The highest wage advantage seems to be for medical graduates in urban sector with 81 percent higher wages than non-graduates, while in the rural sector the wage advantage is positive but insignificant. For engineering graduates the wage returns are significant for both urban and rural sectors with 71 percent and 62 percent higher wages, respectively, relative to non-graduates. It is evident that the wage returns are incremental with higher levels of education, confirming to the findings of earlier studies (Azam 2012). However, the wage advantages for vocational diploma courses (except for vocational diploma 3+ years in rural sample) over non-graduates are higher than what the non-professional graduates have over non-graduates, supporting the earlier findings that technical diploma fetches higher returns than college graduates (Duraisamy 2002, 614-615). On the whole, the wage estimates for all higher education majors and levels seem to be higher in urban sector than in rural sector which is in tandem with the findings of Vatta, Sato, and Taneja (2016).

The dummy variable for gender shows that higher educated women have significant lower wages than higher educated men in all the three samples and rural women incurs the lowest wages. However, the interaction variable shows that the non-professional graduate women, non-professional postgraduate women and professional postgraduate women do have significant positive wage advantage over non-graduate men, in the total and urban samples. The results for all interaction variables in the rural sample are insignificant. Additionally, the interaction estimates for medical and engineering graduate women are positive but not significant. So is the case with vocational diploma holders.

The coefficients of the control variables for demography and occupation status, have the expected signs (table2). The age coefficient is positive and significant indicating positive returns with more years of experience (taking age as a proxy for experience), while the declining returns to experience over time is indicated by the negative age square coefficient, affirming the non-linear pattern of experience-earnings profile (see, also, Duraisamy 2002). The coefficients of socio-religious category are negative and statistically significant only for rural Dalits, Adivasis and urban Muslims. The OBCs have significant negative wages in the total sample. Adivasis are worse off by 18 percent less wage than Brahmins, followed by Dalits and Muslims by16 percent and 9 percent less wages (see, also, Madheswaran and Attewell 2007). As for marital status, the results show that being married have positive effect on wages, whereas, the negative effect of an additional dependent member on wages could be due to the presence of female employees who are more likely to spend more time on child rearing and, therefore, are less likely to have job specific training and, hence, lack in job specific skills leading to their lower pay (see, for example, Mincer and Polachek 1974; Becker 1985). The estimates of log hourly wages for different occupation divisions show that the nine categories of occupation vary in their rewards, in terms of wages, in both the sectors. The estimated results are negative and significant, indicating lower wages for all other occupation divisions except for occupation division two, which is positive and significant, relative to occupation division one. The estimates also point to the gap in wages between various occupations division. The wage premium of professional degree holders over non-graduate workers is obvious from the highest wage gap between occupation divisions one and six. More importantly, the wage premium of professional degree holders over non-professional degree holders is noteworthy as revealed from the negative log hourly wages for occupation division three compared to occupation division one.

Table II Selectivity Corrected Wage Returns

	Total		Rural		Urban	
Explanatory Variables	Log hourly wage	Log hourly wage	Log hourly wage	Log hourly wage	Log hourly wage	Log hourly wage
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Age	0.071***	0.069***	0.033***	0.033***	0.081***	0.080***
	(0.008)	(0.008)	(0.011)	(0.011)	(0.010)	(0.010)
Age square	-0.001***	-0.001***	-0.000*	-0.000*	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Human capital variables						
Non-professional Graduates	**0.176*** **	**0.151*** **	**0.103*** **	**0.090** **	**0.173*** **	**0.150*** **
	(0.022)	(0.024)	(0.034)	(0.036)	(0.027)	(0.030)
Engineering Graduates	**0.742*** **	**0.706*** **	**0.624*** **	**0.584*** **	**0.705*** **	**0.669*** **
	(0.075)	(0.079)	(0.142)	(0.147)	(0.081)	(0.086)
Medical Graduates	**0.767*** **	**0.703*** **	**0.094**	**0.006**	**0.814*** **	**0.806*** **
	(0.117)	(0.137)	(0.251)	(0.261)	(0.123)	(0.151)
Non-professional postgraduates / higher	**0.494*** **	**0.447*** **	**0.383*** **	**0.391*** **	**0.468*** **	**0.412*** **
	(0.036)	(0.040)	(0.053)	(0.057)	(0.044)	(0.049)
Professional postgraduates	**0.542*** **	**0.437*** **	**0.208**	**0.126**	**0.593*** **	**0.489*** **
	(0.062)	(0.068)	(0.134)	(0.145)	(0.065)	(0.073)
Vocational Diploma <3 years	**0.337*** **	**0.310*** **	**0.233* **	**0.175**	**0.286*** **	**0.274*** **
	(0.073)	(0.077)	(0.121)	(0.128)	(0.083)	(0.088)
Vocational Diploma 3+ years	**0.416*** **	**0.411*** **	**-0.096**	**0.030**	**0.524*** **	**0.468*** **
	(0.121)	(0.132)	(0.236)	(0.266)	(0.131)	(0.143)
Others	**0.602*** **	**0.651*** **	**0.522** **	**0.611** **	**0.572** **	**0.614* **
	(0.185)	(0.206)	(0.242)	(0.250)	(0.244)	(0.316)
Gender						
Female	-0.259***	-0.351***	-0.368***	-0.390***	-0.234***	-0.343***
	(0.021)	(0.031)	(0.034)	(0.042)	(0.027)	(0.045)
Interaction variables – human capital & gender						
Non-professional Graduates * female		**0.128*** **		**0.075**		**0.117** **
		(0.046)		(0.077)		(0.059)
Engineering Graduates * female		**0.224**		**0.400**		**0.207**
		(0.184)		(0.444)		(0.201)
Medical Graduates * female		**0.219**		**0.827**		**0.072**
		(0.204)		(0.759)		(0.221)
Non-professional postgraduates / higher * female		**0.173*** **		**-0.037**		**0.195*** **
		(0.057)		(0.101)		(0.071)

Professional postgraduates * female		**0.460*** **		**0.429**		**0.443*** **
		(0.121)		(0.285)		(0.135)
Vocational Diploma <3 years * female		**0.148**		**0.378**		**0.045**
		(0.171)		(0.293)		(0.202)
Vocational Diploma 3+ years * female		**0.032**		**-0.471**		**0.281**
		(0.246)		(0.442)		(0.291)
Others * female		**-0.166**		**-1.119**		**-0.033**
		(0.365)		(0.764)		(0.447)
Demographic variable						
Socio-religious category						
Forward caste	-0.040	-0.037	-0.039	-0.035	-0.021	-0.019
	(0.035)	(0.035)	(0.061)	(0.061)	(0.039)	(0.039)
OBC	-0.083**	-0.080**	0.030	0.032	-0.055	-0.053
	(0.035)	(0.035)	(0.057)	(0.057)	(0.041)	(0.040)
Dalit	-0.161***	-0.161***	-0.325***	-0.324***	0.038	0.041
	(0.047)	(0.047)	(0.082)	(0.082)	(0.050)	(0.050)
Adivasi	0.038	0.039	-0.180**	-0.181**	0.081	0.083
	(0.056)	(0.056)	(0.080)	(0.080)	(0.084)	(0.083)
Muslim	-0.048	-0.044	0.122	0.120	-0.099*	-0.095*
	(0.047)	(0.047)	(0.078)	(0.078)	(0.056)	(0.056)
Other minority religions	0.023	0.026	-0.087	-0.079	0.090	0.094
	(0.057)	(0.057)	(0.096)	(0.096)	(0.066)	(0.065)
Married	0.108***	0.109***	0.153***	0.153***	0.085**	0.085**
	(0.028)	(0.028)	(0.042)	(0.042)	(0.035)	(0.035)
Dependent Boys <12yrs	-0.064***	-0.063***	-0.036**	-0.036**	-0.060***	-0.059***
	(0.012)	(0.012)	(0.017)	(0.017)	(0.017)	(0.017)
Dependent Girls <12yrs	-0.106***	-0.106***	-0.057***	-0.058***	-0.121***	-0.120***
	(0.012)	(0.012)	(0.015)	(0.015)	(0.017)	(0.017)
Dependent Men>65yrs	-0.059***	-0.058***	-0.026	-0.022	-0.052**	-0.053**
	(0.018)	(0.018)	(0.027)	(0.027)	(0.025)	(0.025)
Dependent Women >65yrs	-0.046**	-0.048***	0.013	0.012	-0.056**	-0.058**
	(0.018)	(0.018)	(0.027)	(0.027)	(0.024)	(0.024)
Employment type						
Casual work	-0.365***	-0.366***	-0.342***	-0.345***	-0.347***	-0.346***
	(0.020)	(0.020)	(0.032)	(0.032)	(0.025)	(0.025)
Occupation Division						
Administrative, Executive & Managerial Workers (division 2)	0.321***	0.324***	0.169*	0.176**	0.288***	0.291***
	(0.039)	(0.039)	(0.088)	(0.088)	(0.044)	(0.044)

Clerical & Related Workers (division 3)	-0.091***	-0.093***	-0.163***	-0.164***	-0.108***	-0.110***
	(0.024)	(0.024)	(0.042)	(0.042)	(0.029)	(0.029)
Sales Workers (division 4)	-0.423***	-0.424***	-0.488***	-0.486***	-0.436***	-0.438***
	(0.034)	(0.034)	(0.064)	(0.064)	(0.040)	(0.040)
Service Workers (division 5)	-0.080**	-0.082**	-0.192***	-0.190***	-0.031	-0.036
	(0.039)	(0.039)	(0.060)	(0.060)	(0.050)	(0.050)
Farmers, Fishermen, Hunters, Loggers & Related Workers (division 6)	-0.393***	-0.397***	-0.334***	-0.332***	-0.407***	-0.410***
	(0.038)	(0.038)	(0.048)	(0.048)	(0.107)	(0.107)
Production and Related Workers (division 7)	-0.253***	-0.247***	-0.224***	-0.204***	-0.295***	-0.293***
	(0.050)	(0.050)	(0.077)	(0.078)	(0.064)	(0.064)
Transport Equipment Operators (division 8)	-0.099***	-0.110***	-0.201***	-0.200***	-0.102**	-0.115***
	(0.035)	(0.035)	(0.057)	(0.057)	(0.044)	(0.045)
Labourers (division 9)	-0.267***	-0.278***	-0.293***	-0.291***	-0.223***	-0.238***
	(0.031)	(0.031)	(0.043)	(0.043)	(0.046)	(0.046)
Unclassified	-0.160*	-0.169*	-0.365**	-0.362**	-0.152	-0.163
	(0.095)	(0.095)	(0.176)	(0.175)	(0.110)	(0.110)
Constant	1.803***	1.853***	2.575***	2.584***	1.683***	1.730***
	(0.196)	(0.196)	(0.246)	(0.246)	(0.275)	(0.275)
Observations	8,361	8,361	3,485	3,485	4,876	4,876
Wald chi2	4023***	4087***	1626***	1640***	2232***	2269***
Lambda	0.821***	0.806***	0.728***	0.728***	0.608***	0.594***
Rho	0.876	0.867	0.826	0.827	0.731	0.719
Sigma	0.937	0.929	0.881	0.880	0.832	0.826

Note: Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$; Results of the state dummies are not presented for reasons of brevity

6. Conclusion

This paper examines the varying returns to human capital specified by different levels and majors in non-professional and professional courses under higher education. Unlike in earlier studies, higher education is taken as a heterogeneous sector with varying majors each having varying demand in the labour market owing to skill differences (see, also, Kijima 2006). After correcting for selectivity bias, the Mincerian wage equation is estimated with human capital variables as the main predictors and demographic and occupational variables as additional controls.

The important finding of this study is that there are significant wage premiums for professional degrees especially medical and engineering degrees. This informs us on the concentration of wage premium in technical education owing to higher demand for skilled professionals in medical and engineering professions where much of the technological advancements have taken place. The study finds that medical profession has the highest concentration of skill premium followed by engineering profession, relative to non-graduates. The wage advantages of medical and engineering graduates, relative to non-graduates, seems to be much higher than those of all professional postgraduates. But this is not comparable as the data allows for only aggregate wage returns of all postgraduate courses. Moreover, even when it is found that the wage returns are incremental with higher levels of education, it is not clear whether it is true across all majors. However, it has been earlier found that there are rising skill premia effected through rising levels of education as a consequence of demand shift towards the most skilled (Juhn, Murphy, and Pierce 1993, 432-433). Therefore, it may be inferred that the incremental wage returns to higher levels of education is concentrated to few majors which cater to top end jobs in the occupation hierarchy, leading to wage inequality at the top end of wage distribution (see, also, Juhn, Murphy, and Pierce 1993; Lemieux 2006; Azam 2012). This also supports the inequality increasing effect of higher education on wages (see, for example, Lemieux 2006).

The results of this study have greater implications in the context of the debate on the effects of liberalization on wage inequality, where there are contesting arguments on the increasing and decreasing effects of liberalization policies. On the on hand it is argued that wage inequality has reduced due to increasing wages of unskilled labour than skilled labour, in sectors where more of unskilled labour is employed, due to reduced tariff (Kumar and Mishra 2008, 303). On the other hand, it is posited that wage inequality has increased due to rising skill premium as a consequence of services liberalization (see, for example, Mehta and Hasan 2012). The former is the case of sectors that use more of unskilled labour and the latter is the case of sectors where high skilled labour is used. The present study provides evidences of wage premium for selective high skilled professions, particularly in the service sector, widening the wage gap at the top end occupations with skill premium (see, for example, Lemieux 2006; Azam 2012).

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