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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 overview of existing literature on returns to higher education in India and elsewhere reveals a failure in assessing 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. It is observed that the returns are by and large favouring female professional postgraduates.

1. Introduction

Human capital has long been accepted as crucial for economic growth (Schultz, 1961; Becker 1993) by way of increasing real earnings per worker (Schultz, 1961) thereby reducing poverty (Bloom, Canning & Chan, 2006) and increasing economic output in both developed and developing economies (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 (Kambhampati, 2008).

In India, the analysis of rate of return to higher education shows that higher education contributes significantly to the increasing inequality in wage distribution and hence income inequality. (Lemieux, 2006; Kijima, 2006). Nevertheless, this has not dissuaded an average Indian household from investing in higher education. Presently, the average share of expenditure on higher education out of total household expenditure is 15.3 per cent and 18.4 per cent for rural and urban households respectively (Chandrasekhar, Geetha Rani, and Sahoo, 2016). 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 (Duraisamy & Duraisamy, 1993).

The overview of existing literature on returns to higher education in India fails to assess the probable heterogeneity of returns to higher education across various majors (/disciplines). These studies treat higher education 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 (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

[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 education have their corresponding postgraduate and above degrees.

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. Further, returns by level of education are calculated for graduate degree in general education, post graduate and above degrees and for post graduate degree in professional courses. Additionally, the returns for diploma courses are also calculated. The present analysis draws on extended Mincerian earnings function to estimate the returns to different majors in higher education. The results show highest returns for medical science followed by engineering, law, business administration and chartered accountancy. It is observed that the returns to law, business administration and chartered accountancy and other non-technical education are biased towards females.

The rest of the paper is organised as follows: section two briefly outlines the relevant literature; section three elaborates on the methodological and specification issues; section four describes the empirical specification and methodology; section five details the data and descriptive statistics; section six explains the results; and section seven 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 from 1960 to 1997 of 98 countries (Psacharopoulos and Patrinos, 2004).

In India, the returns to education were found to increase up to secondary level and decline thereafter (Duraisamy, 2002). 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 1983–94 (Duraisamy, 2002).

More recent studies show that returns to education increase with the level of education and is heterogeneous across location, caste and religion (Subbaraman and Von Witzke, 2006; Agrawal, 2012; Geetha Rani, 2014), income quantiles (Azam, 2012), English language ability (Geetha Rani, 2014; Azam, Chin and Prakash, 2013) and cognitive and non-cognitive skills (Heckman, Humphries, & Veramendi 2016). Refuting the results of Duraisamy (2002), Geetha 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 (Azam, Chin and Prakash 2013).

The returns to higher education when disaggregated across quantiles reveal heterogeneity favouring the top quantiles (Azam, 2012; 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, wherein casual workers face flat returns and regular workers have positive and rising returns with education levels (Dutta, P. V., 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). 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 and Sato, 2012).

The varying returns to higher education points to the inequality increasing effect of higher education on wages (Lemieux, 2006) mainly attributed to skill premium resulting from rising demand for skilled labour as a consequence of skilled biased technological change (Kijima, 2006). Interestingly, this wage inequality in concentrated in the top end of the wage distribution (Lemieux, 2006; Azam, 2012). Additionally, education has both market and non-market returns. Heckman, Humphries & Veramendi (2016) finds that both cognitive and non-cognitive endowments affect schooling choices and outcomes. Using a dynamic model of educational choice that account for heterogeneity in cognitive and non-cognitive skills and the continuation values of educational choices, they estimate substantial continuation value components of graduating high school and completing college for high-ability individuals 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 selection bias at all levels of schooling for all outcomes and sorting gains at higher levels of schooling for wage outcomes, supporting the arguments of Becker (1993) that schooling has strong causal effects on market and non-market outcomes.

3. Methodological and Specification issues

3.1 Choice of methodology:

Returns to education are generally estimated by using either "full" or "elaborate method" or "earnings function" method (Psacharopoulos, 1994). Using detailed age earnings profile, the elaborate method calculates the internal rate of returns to education (discounted rates) that equates a stream of education benefits to a stream of education costs at a given point of time (Psacharopoulos, 1994; Duraisamy, P., 2002). The elaborate method is very rarely used for want of data on detailed age-earnings profiles by level of education and cost of education. The most commonly used method is the "basic" earnings function method for estimating returns to education and "extended" earnings function to estimate the returns to education at different levels or even different types of curriculum. The semi-logarithmic earnings function, also known as Mincerian earnings function (Mincer, 1974), rests on four assumptions; First, negligible private direct cost of education (Dougherty & Jimenez, 1991; Duraisamy, 2002); Second, cost of education is the forgone earnings and third, the earnings profiles are isomorphic, i.e., the slope of the earnings function is the same for all levels of education and only the intercept varies (Dougherty & Jimenez, 1991) and lastly, there is no credit market constraint to invest in human capital i.e., credit is available to all at the same interest rate (Schultz, 1988; Duraisamy, 2002).

3.2 Specification Issues:

The Mincerian earnings function holds that individuals' earnings are influenced by level of schooling and on-the-job training measured by job experience (Duraisamy, 2002). The 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. The basic earnings equation is specified as follows:

$$\ln w = \alpha + \beta s_i + \gamma_1 exp_i + \gamma_2 exp_i^2 + \delta X_i + \varepsilon_i \tag{1}$$

where w is the wage rate, s_i is the years of schooling of individual i; exp_i denotes experience of individual i; exp_i^2 denotes experience square of individual i; X_i represents the other additional control variables; and ε_i is the error term which includes the unobserved characteristics that may influence the earnings of individual i. 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 (Basant and Sen, 2014) and schooling outcomes (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 (Krishnan, 1996; Siphambe, 2000). Moreover, market in higher education being characterized by market imperfections (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).

3.3 Selectivity problem:

Above all, like all education models, the above wage equation 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 correct the selectivity bias, Heckman (1979) proposes two-step selectivity correction model based on maximum likelihood method.

4. Empirical Specification and Methodology

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

$$lnw = \alpha + \beta H_i + \beta_1 D_i + \beta_2 O_i + \beta_3 L_i + \varepsilon_i \qquad (2)$$

Where w is the wage rate, H_i represents human capital dummies for different majors and /or degrees in higher education for individual i; D_i denotes demographic characteristics of individual i like age, age square, gender dummies, socio religious category dummies, and dummy variable for marital status; O_i represents occupation dummies 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 natural logarithm of wages is preferred to absolute changes in wages as it reduces the effects of earnings outliers so that the distribution is closer to a normal distribution and is easier to interpret. Since the wage distribution is truncated at zero and is highly right-skewed, if absolute changes in wages are estimated then the estimated result may show people earning negative wages. The coefficients β, β_1, β_2 and β_3 maybe interpreted as the average rate of returns to human capital dummies, demographic variables, occupation dummies and location dummies, respectively. The variables age and age square stand proxy for experience and experience square (Kingdon & Theopold, 2006; Madheswaran & Attewll, 2007) as it is expected that experience increases return but at diminishing rate.

Before estimating the wage rate, it is important to account for selectivity bias. The specification for selectivity correction is elaborated below.

4.1 Selectivity correction procedure:

To account for selectivity issue Heckman's two step procedure is followed. This involves two stages wherein in the first stage the probability to have worked is estimated through a participation (selection) equation. Here an identifying variable is used to mark the exclusion restriction which can affect the selection equation but can be excluded from earnings equation. In other words, the identifying variable should have a strong influence on individuals work participation but no influence on wage earnings. The identifying variables could be non-labour income of the individual or household, family size, land ownership and number of dependent children and elders (Agarwal, 2012). The identifying variables used here are per capita non-labour income of the individual and household size. The non-labour income includes all other incomes except wage and salary[2].

4.1.1 First stage participation equation:

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

$$y_i = x_i\varphi + \mu_i \qquad (3)$$

[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.

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.

4.1.2 Second stage earnings equation:

In the second stage the earnings equation is estimated for individual i holding a higher education degree using ordinary least square (OLS). Here the augmented Mincerian earnings function is used to estimate the wage rates of individuals having higher education in varying majors. 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.

$$lnw = \alpha + \beta H_i + \beta_1 D_i + \beta_2 O_i + \beta_4 L_i + \theta\lambda + \varepsilon_i \qquad (4)$$

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.

5. 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, Dubey 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.

Variables of Interest

The outcome variable is wage rate of individuals with a higher education degree. The independent variables are broadly categorised into demographic variables and human capital variables and occupational variables. 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

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

and other minority religions (Christians, Sikhs, Buddhists, Jains)]; and marital status (unmarried as the reference category).

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 general/non-professional education (BA, BSc, B. Com, etc.); graduate degree in engineering (BE, B. Tech.); graduate degree in medicine (MBBS/BAMS); post-graduate and above degree in general/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 incomplete).

Occupation variables consist of various type of occupation divisions like administrative, executive & managerial workers; clerical & related workers; sales workers; service workers; farmers, fishermen, hunters, loggers & related workers; production and related workers; transport equipment operators; labourers; and unclassified workers.

Table 1 Descriptive Statistics of Variables

Variable	Rural Male		Rural Female		Urban Male		Urban Female	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Wage rate	6664.37	10603.64	5603.71	7400.97	14279.69	17870.38	11499.87	10585.42
Age	33.96	10.72	30.30	8.89	37.61	11.25	33.85	10.38
Age square	1268.35	829.35	997.17	603.74	1541.13	914.22	1253.86	780.63
Non-graduates	0.56	0.50	0.59	0.49	0.41	0.49	0.31	0.46
Non-professional Graduates	0.28	0.45	0.25	0.43	0.38	0.49	0.36	0.48
Engineering Graduates	0.01	0.09	0.00	0.04	0.02	0.15	0.01	0.12
Medical Graduates	0.00	0.05	0.01	0.07	0.01	0.08	0.02	0.13
Non-professional Postgraduate & above	0.12	0.32	0.13	0.33	0.11	0.32	0.24	0.43
Professional Postgraduates	0.01	0.09	0.01	0.10	0.03	0.18	0.04	0.19
Vocational Diploma <3 years	0.01	0.11	0.01	0.12	0.03	0.16	0.01	0.12

Vocational Diploma 3+ years	0.00	0.04	0.00	0.05	0.01	0.09	0.01	0.08
Other	0.00	0.06	0.00	0.03	0.00	0.04	0.01	0.08
Brahmin	0.07	0.26	0.06	0.25	0.11	0.32	0.12	0.33
Forward caste	0.18	0.38	0.21	0.41	0.30	0.46	0.26	0.44
OBC	0.33	0.47	0.30	0.46	0.30	0.46	0.28	0.45
Dalit	0.23	0.42	0.21	0.41	0.15	0.35	0.14	0.35
Adivasi	0.09	0.29	0.09	0.28	0.03	0.17	0.05	0.23
Muslim	0.07	0.25	0.06	0.25	0.07	0.26	0.06	0.24
Other minority religions	0.03	0.16	0.06	0.24	0.04	0.19	0.08	0.27
Married	0.69	0.46	0.53	0.50	0.73	0.45	0.53	0.50
Professional, technical and related workers	0.25	0.43	0.52	0.50	0.08	0.27	0.62	0.49
Administrative, Executive & Managerial Workers	0.02	0.16	0.00	0.06	0.08	0.27	0.03	0.17
Clerical & Related Workers	0.13	0.33	0.11	0.31	0.28	0.45	0.22	0.42
Sales Workers	0.05	0.23	0.01	0.09	0.10	0.30	0.04	0.21
Service Workers	0.04	0.20	0.05	0.21	0.06	0.24	0.02	0.14
Farmers, Fishermen, Hunters, Loggers & Related Workers	0.16	0.36	0.16	0.37	0.01	0.11	0.01	0.10
Production and Related Workers	0.02	0.16	0.07	0.25	0.03	0.18	0.03	0.17
Transport Equipment Operators	0.08	0.26	0.00	0.03	0.10	0.30	0.01	0.11
Labourers	0.25	0.43	0.09	0.28	0.10	0.29	0.01	0.10
Unclassified	0.00	0.07	0.00	0.05	0.01	0.11	0.00	0.06
number of observations	2,876		612		3,774		1,107	

Source: Author's computation

6. Empirical Results

The above extended Mincerian wage equation (equation 2), after selectivity correction, is estimated using ordinary least square method where the natural logarithm of wage of individuals is a function of demographic, human capital and occupation variables. The model is run separately for rural male, rural female, urban male and urban female for ascertaining regional and gender differences. The Mills ratio, the lambda, is positive and significant in rural sample but not significant in urban sample, indicating that the rural sample, and not urban sample, is affected by selectivity bias. The correlation coefficient of the error terms of the participation equation and wage equation are significant for rural sample but not for urban sample (table 2). Meaning, the wages of non-random rural sample is upward biased than a random rural sample, whereas, the wages of urban sample are not affected. The variable of interest here are the human capital variables specified by various levels and majors in higher education. First let us examine the results of demographic variables.

6.1. Demographic characteristics and wage:

The estimated results for most of the demographic variables, after selectivity correction (Table 2), are statistically significant for male whereas most of them are statistically insignificant for females. As expected the age coefficient is positive and significant at 1% level for men and can be interpreted as having positive returns with more years of experience while the declining returns to experience over time is indicated by the negative age square coefficient. The socio-religious category is a category variable with Brahmins as the reference group. The coefficients are negative and statistically significant only for urban male Dalits, Adivasis and Muslims. Adivasis are the most deprived with 43 percent less wage than Brahmins, followed by Muslims and Dalits with 24 percent and 22 percent less wages (Madheswaran and Attewell, 2007). There are positive results for few cases but are not significant. As for marital status, only rural married men show significant positive wage, 22 percent higher wage than the unmarried.

6.2. Human Capital and wages:

The variable of interest in this analysis is the human capital variable denoted by various levels/degrees and majors in higher education – non-professional graduate, medical graduates, engineering graduates, non-professional postgraduates, professional graduates and vocational diploma.

The reference category is non-graduates[4]. The estimates are all positive for all levels and majors though not significant for rural female graduates with medical and engineering majors and vocational diploma 3+ years; and for rural male medical graduates, professional postgraduates and vocational diploma 3+ years among. The estimates show highest gains for urban females with medical majors followed by rural male with engineering majors. Urban females seem to be gaining high with medical degree earning 127 percent more wages than all non-graduates followed by urban male medical graduates with 103 percent higher wages than non-graduates. In engineering majors, rural men are at an advantage with 115 percent higher wages than non-graduates followed by urban female and male graduate engineers with 80 and 72 percent higher wages, respectively, than non-graduates.

The wage difference across degree levels reveals that medical graduates command highest wage followed by engineering graduates which is followed by professional postgraduates and then by non-professional postgraduates and above. Interestingly, medical and engineering graduates command higher pay than postgraduates and above non-professionals. Non-professional graduates, and vocational diploma holders among rural female seem to be earning more wage than their urban counter part with similar degree. In general, higher education wages seem to be positively skewed towards females in urban cases. Particularly, the high earning degrees seem to be positively biased towards females in urban sector with higher wages for female medical (127 percent) and engineering (81 percent) graduates, and professional postgraduates (116 percent). Furthermore, higher education seems to be remunerated better in urban sector than in rural sector

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

as indicated by higher wages in urban sector for most of the degrees confirming to the findings of Vatta and Sato (2012), whereas the diploma courses are remunerated higher in rural sector.

6.3. Occupation division and Wage:

Occupation divisions are taken as additional control variable. The estimates of log wages for different occupation division (based on National Occupational Classification 1968) is also calculated with occupation division one (professional, technical and related workers) as the reference category. The estimated results are negative and significant for all other occupation divisions except for occupation division two (administrative, executive & managerial workers) which is positive and significant. In other words, except for occupation division two, all other occupation divisions have lower wages than occupation division one. The estimates also point to the gap in wages between various occupations division. The wage premium of professional degree holders over workers without any degree is obvious from the highest wage gap between occupation divisions one and six (Farmers, Fishermen, Hunters, Loggers & Related Workers). More importantly, the wage premium of professional degree holders over non-professional degree holders is noteworthy as revealed from the negative log wages for occupation division three compared to division one.

Table 2 Selectivity Corrected Wage Returns

	Rural male	**Rural female**	**Urban male**	**Urban female**
VARIABLES	log wage	log wage	log wage	log wage
Demographic Variables				
Age	0.054***	0.021	0.100***	0.067**
	(0.017)	(0.041)	(0.014)	(0.030)
Age square	-0.000**	0.000	-0.001***	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Socio Religious Category				
Forward caste	0.083	-0.174	0.068	0.074
	(0.110)	(0.195)	(0.064)	(0.101)
OBC	-0.054	-0.151	-0.022	-0.025
	(0.102)	(0.192)	(0.066)	(0.106)

Dalit	0.127	-0.040	-0.218***	0.150
	(0.138)	(0.196)	(0.077)	(0.147)
Adivasi	-0.008	-0.140	-0.432***	0.177
	(0.140)	(0.225)	(0.131)	(0.222)
Muslim	-0.065	-0.135	-0.237***	-0.003
	(0.139)	(0.264)	(0.090)	(0.143)
Other minority religions	0.186	-0.262	0.034	0.208
	(0.181)	(0.261)	(0.113)	(0.139)
Marital status				
Married	0.221***	0.130	0.049	0.191
	(0.073)	(0.106)	(0.056)	(0.122)
Human Capital Variables				
Higher Education				
Non-professional Graduates	0.240***	0.331**	0.304***	0.342***
	(0.060)	(0.131)	(0.044)	(0.075)
Engineering Graduates	1.155***	0.458	0.728***	0.807***
	(0.247)	(0.606)	(0.126)	(0.253)
Medical Graduates	0.160	0.985	1.030***	1.274***
	(0.439)	(1.015)	(0.225)	(0.279)
Non-professional postgraduates & above	0.554***	0.440***	0.434***	0.628***
	(0.096)	(0.145)	(0.069)	(0.095)
Professional postgraduates	0.298	0.994**	0.492***	1.161***
	(0.247)	(0.401)	(0.108)	(0.170)
Vocational Diploma <3 years	0.457**	0.847**	0.350***	0.513*
	(0.211)	(0.397)	(0.124)	(0.262)
Vocational Diploma 3+ years	0.071	0.267	0.688***	1.269***
	(0.461)	(0.610)	(0.207)	(0.345)
Others	1.087***	1.874*	0.022	0.805*
	(0.406)	(1.014)	(0.461)	(0.488)
Occupation Division				
Administrative, Executive & Managerial Workers	0.307*	0.961*	0.367***	0.476***
	(0.163)	(0.504)	(0.075)	(0.154)
Clerical & Related Workers	-0.172**	-0.148	-0.088	0.191***
	(0.082)	(0.141)	(0.054)	(0.072)
Sales Workers	-0.630***	-1.055***	-0.528***	-0.049
	(0.118)	(0.369)	(0.070)	(0.140)
Service Workers	-0.423***	-0.121	-0.108	-0.261
	(0.118)	(0.208)	(0.085)	(0.191)
Farmers, Fishermen, Hunters, Loggers & Related Workers	-3.498***	-3.680***	-2.367***	-2.846***
	(0.088)	(0.136)	(0.184)	(0.318)
Production and Related Workers	-1.485***	-1.999***	-1.062***	-2.316***
	(0.158)	(0.219)	(0.114)	(0.178)
Transport Equipment Operators	-1.338***	0.494	-0.759***	-0.050
	(0.103)	(0.671)	(0.074)	(0.268)
Labourers	-2.831***	-2.817***	-1.364***	-1.736***
	(0.076)	(0.153)	(0.076)	(0.305)
Unclassified	-1.319***	0.130	-0.295	0.070
	(0.332)	(0.671)	(0.182)	(0.453)
Constant	7.678***	7.556***	7.086***	6.047***
	(0.391)	(0.815)	(0.359)	(0.868)
Observations	2,876	612	3,774	1,107
Wald chi2	5064	1763	2052	838

Lambda	0.717***	0.687*	0.0111	0.639

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

7. Conclusion

This paper examines the varying returns to human capital specified by different streams of technical education under higher education. Unlike in earlier studies, higher education is taken as a heterogeneous sector with various majors each having varying demand in the labour market owing to skill differences. After correcting for selectivity bias, the Mincerian wage equation for wage is estimated with demographic and human capital variables as the predictors. As indicated by demographic variables, the study finds that caste and religious identity have a detrimental effect on wages of individuals from lower castes and minority religion, confirming to earlier studies (Madheswaran and Attewell, 2007).

The human capital variables of higher education degrees and majors reveal that there is a significant wage premium for medical degree than engineering degree, especially for urban females who reap the benefits of higher wages than urban male. All other professional/technical degrees taken together have lower wage returns than medical and engineering degree. This is more so in urban sector, where higher education seems to be better remunerated because of demand for certain skills in the labour market.

The policy implication of this paper lies in the fact that it informs the government on the heterogeneous outcomes of higher education as revealed by the varying returns to different majors within technical education. Accordingly, the government may formulate policies to decide on the level of investment needed in each streams of technical education as well as non-technical education.

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Appendix A1 Wage Returns without Selectivity Correction

Variables	Rural male	Rural female	Urban male	Urban female
Demographic Variables				
Age	0.044***	0.013	0.091***	0.025
	-0.015	-0.034	-0.012	-0.021
Age square	-0.000**	0	-0.001***	0

	0	0	0	0
Socio Religious Category				
Forward caste	0.253**	0.146	0.051	0.063
	-0.112	-0.193	-0.065	-0.1
OBC	0.007	0.014	-0.037	0.006
	-0.106	-0.192	-0.068	-0.105
Dalit	-0.226**	0.177	-0.231***	0.023
	-0.109	-0.198	-0.075	-0.117
Adivasi	-0.179	-0.133	-0.365***	-0.076
	-0.133	-0.235	-0.137	-0.219
Muslim	-0.015	-0.028	-0.338***	0.02
	-0.137	-0.233	-0.092	-0.147
Other minority religions	0.221	-0.43	0.034	0.135
	-0.194	-0.263	-0.111	-0.133
Marital status				
Married	0.227***	-0.117	0.042	0.089
	-0.072	-0.097	-0.057	-0.07
Human Capital Variables				
Higher education				
Non-professional Graduates	0.243***	0.402***	0.293***	0.359***
	-0.059	-0.113	-0.044	-0.073
Engineering Graduates	0.946***	0.984	0.675***	0.769***
	-0.271	-1.053	-0.128	-0.246
Medical Graduates	0.331	1.411**	1.095***	0.957***
	-0.466	-0.563	-0.245	-0.233
Non-professional postgraduates & above	0.503***	0.366**	0.447***	0.574***
	-0.09	-0.15	-0.067	-0.086
Professional postgraduates	0.013	1.192***	0.437***	1.083***
	-0.272	-0.397	-0.108	-0.161
Vocational Diploma <3 years	0.502**	0.505	0.343***	0.469*
	-0.226	-0.358	-0.119	-0.248
Vocational Diploma 3+ years	0.117	0.433	0.640***	1.267***
	-0.565	-0.791	-0.209	-0.351
Others	0.53	1.812	0.015	0.44
	-0.398	-1.397	-0.521	-0.377
Occupation division				
Administrative, Executive & Managerial Workers	0.440***	0.564	0.348***	0.413**
	-0.164	-0.659	-0.077	-0.176
Clerical & Related Workers	-0.154*	-0.367***	-0.116**	0.144*
	-0.087	-0.141	-0.055	-0.075
Sales Workers	-0.216*	-1.652***	-0.556***	-0.099
	-0.122	-0.451	-0.072	-0.145
Service Workers	-0.653***	-0.034	-0.121	-0.510**
	-0.133	-0.2	-0.087	-0.209
Farmers, Fishermen, Hunters, Loggers & Related Workers	-3.484***	-3.676***	-2.558***	-3.170***
	-0.092	-0.147	-0.178	-0.302
Production and Related Workers	-1.611***	-1.944***	-1.053***	-2.142***
	-0.165	-0.191	-0.109	-0.174
Transport Equipment Operators	-1.278***	0.906	-0.718***	-0.037
	-0.108	-1.127	-0.075	-0.261
Labourers	-2.838***	-2.764***	-1.383***	-1.663***
	-0.079	-0.162	-0.076	-0.288

Unclassified	-1.616***	-0.228	-0.289	-0.03
	-0.36	-0.796	-0.179	-0.494
Constant	8.142***	7.903***	7.358***	7.286***
	-0.326	-0.575	-0.334	-0.446
Observations	2,876	612	3,774	1,107
R-squared	0.634	0.782	0.355	0.466
F-statistic	85.79	35.52	35.88	16.08

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1