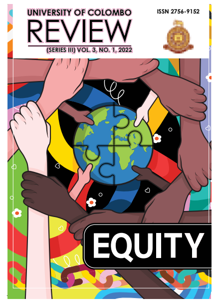

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Analyzing wage differentials by fields of study: Evidence from Sri Lanka

Priyanga Dunusinghe
Senior Lecturer, Department of Economics, University of Colombo

ABSTRACT

Aspirants of higher education and their parents often face a dilemma over the selection of a field of study which pays off handsomely in the job market. This article is based on a study which investigated investigates graduate wage differentials associated with primary employment by fields of study. It employed both mean and quantile regression specifications to the nationally representative labour force survey data. The study found Engineering, Medicine, Management, Commerce, and Law graduates enjoy statistically significant positive wage premiums compared to graduates of Arts. Moreover, these wage premiums are relatively larger in the upper segment of the graduate wage distribution compared to the lower segment. Relatively smaller and statistically weaker wage premiums were observed for Science and Information Technology fields of study whereas graduates of Agriculture and Indigenous Medicine do not enjoy a wage premium over graduates of Arts. The study also found a significant gender pay gap in Management, Commerce, and Science fields of study.

KEYWORDS:
Graduate wage differentials, fields of study, gender wage-gap, Sri Lanka.

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✉ dunusinghe@econ.cmb.ac.lk

Introduction

Why do individuals receive different wages in the labour market? Labour Economics, based on the pioneering work of Mincer (1974), has attempted to explain the factors that contribute to the presence of wage differentials in the labour market. In the early years, most researchers explained the factors that result in wage differentials among labour market participants by employing various individuals, household levels, and other factors. The standard of human capital, measured in terms of years of schooling and experience, emerged as one of the key explanatory factors of the wage differentials (Tachibanaki, 1998). In addition, several socio-economic, demographic, and labour market-related factors have been identified in explaining the differentials unaccounted by human capital stock.

In recent years, researchers began to explore wage differentials in the fields of study in tertiary education on the basis that years of schooling are not the prominent variable in these instances (Bratti et al., 2005; Chevalier, 2011; Görlitz & Grave, 2012; Kelly et al., 2010). These researchers document heterogeneity in returns to tertiary education across the field of study. The investigations on returns for fields of study in tertiary education commenced in developed countries. Recently it has emerged as a stimulating research area in developing countries.

The Sri Lankan state provides free education from Grade 1 to a basic university degree regardless of the field of study. The current student evaluation system at the school level has three major national level examinations: the Grade 5 scholarship examination, the General Certificate Examination of Ordinary Level (GCE O/L), and the General Certificate Examination of Ordinary Level (GCE A/L). The students are broadly free to select their field of study, for the university and beyond, after completing the GCE O/L examination. Additionally, students can select their fields of study based on their GCE A/L achievements. It is important to note that, in most cases, admission to state universities is based on a district quota system where cut-off marks for each district are announced by the University Grant Commission (UGC) every year. Moreover, admission to specific fields, based on GCE A/L subject streams is determined by the UGC. Hence, while the students can indicate their preferences, they have limited opportunity to make a final decision about the university that they enrol into and the fields of study that they pursue at the university entrance stage. At the university level, based on students' academic performance, there exists a limited opportunity for further specialization. At all these levels, information on returns to various fields of studies would be immensely useful for students as well as their guardians to make optimal decisions. Similarly, information on relative returns would be useful for policymakers to decide the optimal allocation of limited resources. Nevertheless, as far as the author knows, returns to various fields of study have not been investigated in the context of Sri Lanka. Therefore, information crucial for optimal allocation of human and financial resources is lacking. Our study aimed at filling the above gap by investigating the wage differentials associated with specific fields of study within a university degree. Associated with a university degree. Different levels of performance of the degree-awarding institutions, vocational and professional training programmes were beyond its scope.

Literature survey

The effect of education on earnings is significant across time and space (Psacharopoulos & Patrinos, 2018). Therefore, more educated workers substantially earn more than their peers who are less educated. Therefore, analyzing what factors affect wage differentials by the field of study among university graduates is emerging as an attractive research area. The seminal findings of Mincer (1974) motivated many researchers to estimate returns to education in subsequent years (Heckman, et. al., 2003). According to Mincer, the rate of return to education is the extra earnings of a worker for an additional year of schooling and training (1974).

Spending on education is an investment in an individual's human capital to increase his or her earnings (Mincer, 1974). Many studies confirm that educated individuals earn higher than their less-educated peers (Patrinos and Psacharopoulos, 2004). Therefore, wage differentials that correlate to the level of education motivate people to invest in education. Human capital is concerned with knowledge, skills, capabilities, and attributes embedded in an individual which are gained by education, training, and experiences. Such capital facilitates the creation of personal, social, and economic well-being (Todaro and Smith, 2012, Giziene et al., 2012). As human capital generates returns through the production process it signifies the capital component (Schultz, 1971). The Mincerian wage equation is constructed based on compensating differentials model and accounting identity model (Mincer, 1958).

The theory of compensating differentials explains why persons with different levels of schooling receive different earnings. Here the author assumed that individuals have identical abilities and opportunities, but different occupations differ in terms of the amount of training required. Since longer periods of training involve an opportunity cost, higher compensations are expected for such jobs. Mincer (1974) introduced his second model with a different set of assumptions from his earlier model. This model was first developed by Becker in 1964. According to Becker and Chiswick (1966), the model focuses on the life cycle dynamics of wages and the relationship between perceived earnings and potential earnings, human capital investment at school, and on the job. Mincer assumes that potential earnings in any period depend on previous investments. More specifically, earnings are a function of potential earnings net of human capital investment cost (Mincer, 1974). However, the earnings specification of the two models is algebraically similar.

Human capital literature analyzes the rate of return to education both at the micro-and macro-level (Psacharopoulos, 1985). Patrinos and Psacharopoulos (2004) update the return to investment in education by presenting the latest estimates and patterns. The findings suggest that investment in education behaves similarly to investment in physical capital. Patrinos and Psacharopoulos (2004) used empirical evidence on returns to education to measure the productivity of education. The results show that skills, ability, and learning outcomes affect earnings.

In the context of tertiary education, Grave and Gorlitz (2012) found that graduates from Arts earn lower average monthly wages compared to the other fields of study. Accordingly, Arts graduates receive an average monthly wage that is 26 per cent lower than the wage of a Science graduate and 40 per cent lower than the wage of an Engineering graduate. Interestingly, the authors found that the above wage differentials could be explained by different job and firm characteristics rather than individual or study-related characteristics. The authors concluded that the less favorable jobs and firm characteristics of Arts graduates at labour market entry may persist for around 5-6 years.

Bol and Heisig (2021) examined wage differentials by field of study among higher education graduates in a sample of 29 countries. The authors found that numeracy skills of STEM (Science, Technology, Engineering, and Mathematics) graduates make them eligible for employment with higher monthly wages. In particular, this study found that specific skills, proxied by skills used on the job, explain a substantial portion of between-field wage differentials. Similarly, Paola and Tansel (2017) found the existence of important wage differences in the field of study in Turkey.

In contrast to previous aforementioned literature, Tran and Vu (2020) found that graduates of Engineering, Science, Mathematics, Computer Science, Business, and Finance earn lower salaries than the Arts and Humanities graduates. The study concluded that wage differentials are greater among females than among male graduates. These findings are contradictory to the conventional claim that STEM fields generally have higher returns in the labour market.

While university degrees differ in terms of fields of study, they also vary in terms of the level of educational achievement, i.e. whether the student graduates with honours or not. Extending the research frontier further, Freuer et. al. (2015) examined the returns to graduating with honours among law graduates. The study found that law graduates who passed the state bar exam with an honors degree receive a significant earnings premium of about 14 per cent. Moving beyond country-specific evidence, Miroslav et.al. (2015) studied returns to university degrees in five European countries, namely France, Italy, Hungary, Poland, and Slovenia. The authors found that after taking into account opportunity costs, enrolling in STEM degrees is often not the best investment for students, in particular for female students. The authors argue that students often make decisions based on private returns and if the policymakers wish to change students' behaviour it is important to change the incentives offered.

Ciftci and Ulucan (2021) analyzed returns to college majors using both Ordinary Least Square (OLS) and quantile regression framework after correcting the selection bias. The authors found that, except for Medicine and Engineering, returns to other natural sciences and technical majors remain somewhat lower compared to Arts and other fields of study. Therefore, Ciftci and Ulucan (2021) argue that the skill-biased technology change hypothesis is not valid in the wage profile in Turkey. They note that the supply of those majors exceeds the market demand. Machin and Puhani (2003) studied the wage gap between male and female graduates by the subject of degree. They identify a 2 to 4 per cent gender wage gap between the two groups. Accordingly, male graduates tend to earn higher than female graduates irrespective of their fields of study (Machin and Puhani, 2003).

Hamermesh and Donald (2008) analyze the impact of the college major on earnings. Montt (2017) found differentials in returns by the field of study in the Irish labour market depending on various job-related capabilities which can be acquired at the completion of higher education. It further analyzes the variation of returns across the income distribution. The results of the quantile regression show that based on the field of study and the level of competencies the returns vary across the income distribution. According to Lemieux (2014), wage differentials commonly depend on occupation and field of study. The study found three reasons behind the returns to investment in education. The first reason is within the traditional human capital framework which says that education helps workers to be more productive on a given task. The second reason emphasized the importance of education as it supports the workers to engage in higher-paying jobs where the output relates to their skills. The third reason is that when the workers are matched to a job according to their field of study, they become more productive and earn more. The third and the second reasons marked a return on education close to half of the conventionally measured return to education. It also highlights the return on investment in education differentiate based on occupation and the field of study. Wage differentials of graduates not only depend on the field of study but also on the quality of the educational institution and educational performance.

Econometric specification and sata

Mean regression

Heckman et. al., (2003) observes that the Mincerian earnings regression framework is used in the literature to estimate returns to schooling, returns to schooling quality, and to measure the impact of work experience on the male-female wage gap. Theoretically, the Mincerian framework captures two distinct economic concepts: (a) a pricing equation or hedonic wage function revealing how the labour market rewards productive attributes like schooling and work experience, and (b) the rate of return to schooling which can be compared with the interest rate to determine optimality of human capital investments (Heckman, et.al., 2003).

The general form of the earnings equation states that earnings are a function of schooling and labour market experience. It is possible to employ this framework in understanding wage differentials, if any, across different fields of study. Based on the Mincerian framework, this study specifies the following regression equation to examine the wage differential by field of study at the mean;

$$y = X\beta + \varepsilon \qquad (1)$$

In eq. (1), y is a vector, the dependent variable, representing log hourly wage, and X is a matrix consisting of variables such as age, age-square, the highest level of education, gender, ethnicity, and marital status. In addition, X contains a set of dummies representing different fields of study. In Eq. (1) β is a coefficient vector and ε is the iid disturbance term vector.

Correcting selection bias

It is a well-known fact that nationally-representative samples are not selected on a random basis; rather, they are designed using stratified sampling techniques to reflect population characteristics. Hence, it is important to address the selection bias issue when estimating a behavioral relationship. The following discussion provides a brief note on the selection bias correcting approach adopted in this study. The essence of this illustration is based on Bourguignon et al. (2007, pp. 175-79).

Consider a situation in which an individual chooses whether to participate in the labour market where each participant may select among j mutually exclusive alternatives. These alternatives could be (i) economically inactive, (ii) employed, and (iii) unemployed. In this paper, the informal sector consists of self-employed and unpaid family workers. This is rather a narrow definition). Let Y_j^* be the utility attainable for an individual if he/she chooses alternative j. We can write the indirect utility function as,

$$Y_j^* = Z\gamma_j + \epsilon_j, \qquad j = 1, 2, \ldots, J, \tag{2}$$

where the matrixZ represents a set of explanatory variables affecting employment alternatives, and ϵ_j is the error term. A rational individual compares the utility attainable from each alternative and selects the alternative s that gives him the highest benefits, that is:

$$Y_s^* > \max_{j \neq s}(Y_j^*), \qquad s \in (1, 2, \ldots, J) \tag{3}$$

Assume the market wage in the sth alternative is given by:

$$ln\mathrm{w}_s = X_s\beta_s + \mathrm{u}_s, \tag{4}$$

whereX_s is a matrix containing exogenous variables (including fields of study dummies) that determine the log hourly wage (lnw_s), and the disturbance is an i.i.d. random variable with zero mean [E(u_s|X,Z)=0] and a constant variance [V(u_s|X,Z)=σ_s^2]. If there are unobserved characteristics that affect both individuals' choices and their earnings, it could be proved that the disturbance ϵ_j in eq. (1) and disturbance u_s in eq. (4) are correlated (Bourguignon et al., 2007).

As Hecman (1979) pointed out, the potential inconsistency requires a correction for selection bias when estimating a behavioral relationship such as eq. (1). There are several approaches in the literature for correcting the selection bias problem (Dahl, 2002; Dubin and MaFedden, 1984; Lee, 1983). Among them, Dubinand and MaFadden's (1984) (henceforth DMF) approach is popular as well as relatively superior to the other methods (Bourguignon et al., 2007). The DMF approach does not assume the direction of the correlation and uses multiple correction terms to control the self-selection in the sth alternative as related to each other alternative. Hence the correlation between u_s and (ϵ_j-ϵ_s) could be of different signs for different j. Similarly, the DMF approach identifies not only the direction of the selection bias but also where the bias stems from, by linking the selection bias to the allocation of individuals to each alternative. Due to these reasons, this study employs the DMF approach for selection bias correction. According to the DMF method, consistent estimates that are free from sample selection could be derived by estimation eq. (5).

$$lnw_s = X_s\beta_s + \sigma_s \frac{\sqrt{6}}{\pi} \sum_{j \neq s} r_j \left[\frac{p_j \ln(p_j)}{1 - p_j} + \ln(p_s) \right] + e_s \quad (5)$$

Where r_j is the correlation coefficient between disturbance u_s and ϵ_j, and e_s is a residual whose asymptotic mean is zero. Eq. (5) can be estimated in two steps. In the first step, the polychotomous choice mode is estimated by the logit maximum likelihood method (eq. (2)). Let p ̂_(j,) be the predicted probabilities for p_j, j=1,…,J. In the second step, we substitute p ̂_(j,), j=1,…,J (the selectivity correction term) into eq. (5) and we then estimate the function by OLS. Since this involves a two-step procedure, the estimated standard errors may not be efficient. To correct it one may use the weighted estimation and bootstrap procedures to obtain robust standard errors. We estimate the eq. (1) in the form of eq. (5) and use the bootstrap method for obtaining the robust standard errors.

Quantile regression

As Buchinsky (1994) suggests, mean regression techniques have never been satisfactory approaches to analysing heterogeneous populations. To consider the potential heterogeneous impacts, this study specified the qth – quantile (0< q<1) of the conditional distribution of the dependent variable, given a set of variables Xs as follows:

y_q=Xβ_q+ ε_q (2)

Cameron and Trivedi (2009) show that estimation of equation (1) based on the qth quantile regression involves minimizing the absolute value of the residual using the following objective function:

$$Q_N(\beta_q) = \min_{\beta} \sum_{i=1}^{N} [|y - X^{\prime}\beta_q|] = min \left[\sum_{i:y \geq X^{\prime}\beta_q} q|y - X^{\prime}\beta_q| + \sum_{i:y < X^{\prime}\beta_q} 1 - q|y - X^{\prime}\beta_q| \right] \quad (3)$$

Data and data sources

This study used Labour Force Survey (LFS) 2017 & 2018 data, collected and disseminated by the Department of Census and Statistics (DCS) of Sri Lanka, for estimating the above regression models. It considered two survey years since the number of observations and graduates from different fields of study were limited to a single survey. The LFS is a nationally representative survey that collects data quarterly and covers around 25,000 households in a year. It gathers demographic, education, and labour market-related data for all the individuals residing in a selected household. Labour market-related data is collected for people aged 15 and above. It covers areas such as labour force participation, employment, unemployment, underemployment, labour market informality, social security contribution, secondary job holdings, wages and remuneration, and training. The LFS also collects data on the highest level of education completed by individuals who are not currently engaged in full-time studies.

Based on the above information, the our study draws a sample of individuals who possess university degrees. The sample consists of graduates who are either employed, unemployed, or economically inactive. These three groups are considered under the selection bias correction model, i.e. Eq. (5). The log hourly wage is considered as the dependent variable where the monthly wage is converted to hourly wages by using the usual hours of work per week. For a daily-paid worker, the monthly wage is calculated as the daily wage rate multiplied by the number of days worked per month. Usual hours of work are multiplied by 4.2 weeks to get the usual hours of work per month. For a monthly-wage earner, the monthly gross salary (including all usual receipts) is considered.

The study only considers the wages earned in primary employment (According to LFS 2018, secondary job holding among graduates is around 2 per cent. It seems secondary job holding is somewhat under-reported in the survey). Several explanatory variables such as age, age square, and dummy variables representing ethnicity, industry, occupation, gender, sector, English proficiency, vocational/professional training status, and year are considered. Key variables of interest, the fields of study, are introduced into the model as dummy variables. The study considers 10 fields, namely Arts, Law, Management, Commerce, Science, Agriculture, Medicine, Indigenous Medicine, and Computer Science. In addition, the study considers further fields of study under the category 'other' since the number of observations was limited. The LFS also collects data on postgraduate qualifications and a dummy variable is introduced into the regression model to capture earnings differentials, if any, attributed to a postgraduate qualification.

Estimation and discussion

Descriptive statistics

Figure 1 depicts the distribution of graduate log monthly wages by fields of study. Accordingly, Arts graduates' mean is lower compared to the mean wage of all the other fields indicating, on average, that Arts graduates earn less in the labour market. In contrast, Medical graduates' mean wage is right to the mean wage of all the other fields of study. This implies, on average, that medical graduates receive higher wages compared to graduates of all the other fields of study. Moreover, the mean wage of Agriculture graduates is somewhat closer to the mean wage of Arts graduates. It may suggest that the wage differentials between Arts and Agriculture graduates may be either very small or completely absent. Similarly, the mean wage of Science graduates is marginally higher than that of the Arts graduates. These may imply that Arts, Agriculture, and Science graduates hold jobs that are paid equally and require a similar set of skills.

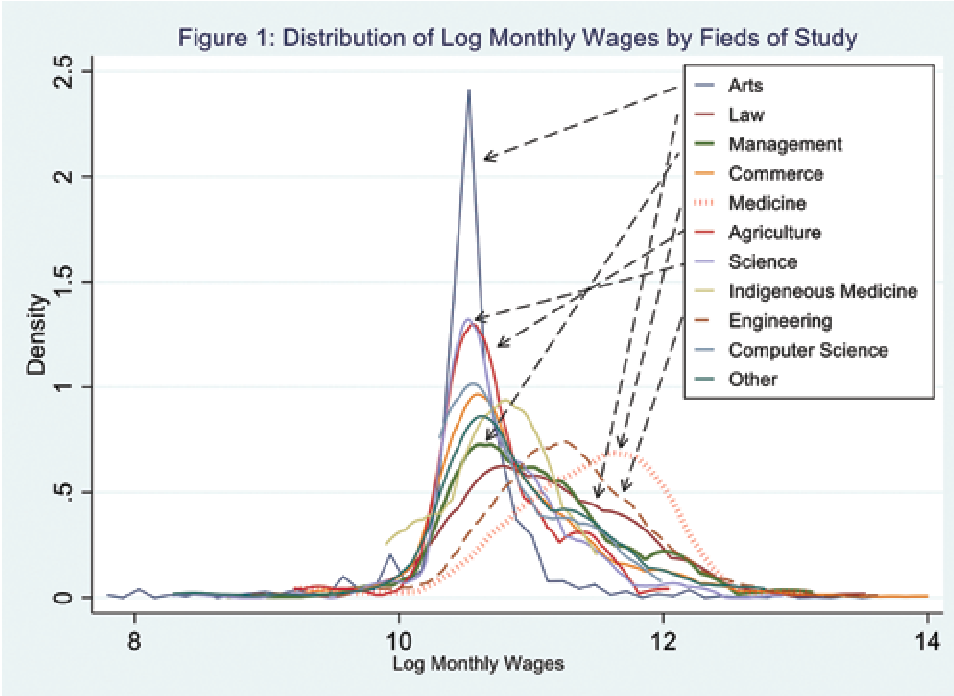

Figure 1: Distribution of Log Monthly Wages by Fieds of Study

Source: Author's construction based on Labour Force 2018

Arts graduates are generally in a disadvantaged position compared to graduates of most other subject streams. For instance, relative to the average hourly wage of all female graduates, females who have read for an Arts degree earn an average hourly wage rate that is 13 per cent lower. In contrast, female graduates who follow Law, Medicine, and Engineering degrees receive 80 per cent, 68 per cent, and 88 per cent, respectively, higher wage rates compared to the hourly wage rate of all other female graduates. Similarly, male Arts graduates receive an hourly wage rate that is 27 per cent lower compared to the average hourly wage rate of other male graduates. Male graduates who read for Law and Medicine degrees receive around 50 per cent higher wage rates compared to the average hourly wage rate of other male graduates.

Management and Engineering male graduates earn an hourly wage rate that is about 25% higher than that of the average male wage rate of all subject streams. Among the male graduates, in 2017-18, Indigenous Medicine graduates earn the lowest hourly wage rate followed by male Arts and Agriculture graduates (see Table 1). Relative to the average hourly wage rate of all graduates, male Indigenous Medicine graduates earn the lowest wage rate followed by female Arts graduates. In contrast, male Arts graduates earn a 16 per cent lower hourly wage rate compared to the average hourly wage rate of graduates of all subject streams (see Table 1). Overall, graduates who have followed Arts, Indigenous Medicine, Agriculture, Computer Science, and Science earn a lower wage rate compared to the average hourly wage rate of all graduates. However, these differentials could be due to many observable and unobservable characteristics and the subject stream may explain only a part of such differentials. The regression analysis is expected to account for some of the observable characteristics such as gender, English proficiency, labour market experience (captured by age of the graduate), postgraduate qualifications, industry, and occupation. Hence, it is expected that the regression analysis will capture part of the wage differentials attributable to the subject stream of the graduates.

Table 1: Relative wage differentials

Study stream	% of wage gain or loss				
	Relative to the average hourly wage of all female graduates	Relative to the average hourly wage of all male graduates	Relative to the average hourly wage of all graduates		
	Female	Male	Female	Male	All
Arts	-13.2	-27.2	-24.4	-16.1	-21.7
Law	80.2	50.1	56.9	72.9	63.4
Management	10.2	24.3	-4.1	43.2	23.4
Commerce	-1.0	16.7	-13.8	34.5	10.9
Medicine	67.7	49.5	46.0	72.2	60.2
Agriculture	-11.7	-24.5	-23.2	-13.1	-17.6
Science	0.6	-14.9	-12.4	-1.9	-6.7
Indigenous medicine	1.4	-51.7	-11.7	-44.3	-23.8
Engineering	88.4	25.2	64.0	44.2	47.7
Computer	2.3	-18.9	-11.0	-6.5	-7.6
Other	9.2	8.6	-4.9	25.1	11.4

Source: Author's construction based on LFS, 2017 and 2018

Table 2 reports some summary statistics of variables that will be considered in the regression analysis. In our sample of data, nearly 43% is male and the larger majority of graduates fall into the 30-44 age group. Nearly half of the graduates in the sample have followed an Arts degree while around 11% of graduates have pursued a Management degree. The share of graduates who have read for a Computer Science or Indigenous Medicine accounts for around 1 per cent each respectively. Nearly 88% of graduates are employed in the services sector and nearly 52% engage as professionals in the labour market. It is also interesting to note that nearly 85% of all graduates could read and write in English and, importantly, nearly 16% of graduates have obtained a postgraduate qualification. The above sample characteristics show that the sample represents the graduate population reasonably. The LFS does not collect data on grades – General Point Average (GPA) or the class (1st, Second Upper, Second Lower, etc.) and degree awarding institute (Public vs. Private university) and place of graduation (foreign vs. local university). Collecting details of the above factors is important to engage in a more nuanced analysis of graduate wage differentials in the future.

Table 2: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Hourly wage (in log)	3,161	5.63	0.56	3.42	8.50
Gender (Male=1)	4,206	0.43	0.50	0.00	1.00
By age groups:					
15-29	4,206	0.21	0.41	0.00	1.00
30-44	4,206	0.43	0.49	0.00	1.00
45-59	4,206	0.23	0.42	0.00	1.00
60+	4,206	0.13	0.33	0.00	1.00
By study stream					
Arts	4,206	0.48	0.50	0.00	1.00
Law	4,206	0.02	0.15	0.00	1.00
Management	4,206	0.11	0.31	0.00	1.00
Commerce	4,206	0.09	0.29	0.00	1.00
Medicine	4,206	0.03	0.18	0.00	1.00
Agriculture	4,206	0.02	0.14	0.00	1.00
Science	4,206	0.08	0.28	0.00	1.00
Indigenous medicine	4,206	0.01	0.09	0.00	1.00
Engineering	4,206	0.05	0.22	0.00	1.00
Computer science	4,206	0.01	0.11	0.00	1.00
Other	4,206	0.08	0.28	0.00	1.00
Postgraduate qualification (1=Yes)	4,206	0.16	0.37	0.00	1.00
By economic sector					
Agriculture	3,238	0.02	0.15	0.00	1.00
Industry	3,238	0.10	0.30	0.00	1.00
Services	3,238	0.88	0.33	0.00	1.00
By occupation					
Manager	3,238	0.15	0.36	0.00	1.00
Professional	3,238	0.52	0.50	0.00	1.00
Technician	3,238	0.22	0.41	0.00	1.00
Clerk	3,238	0.06	0.23	0.00	1.00
Sales	3,238	0.02	0.14	0.00	1.00
Skilled agriculture	3,238	0.01	0.11	0.00	1.00
Craft	3,238	0.01	0.10	0.00	1.00
Operators	3,238	0.00	0.04	0.00	1.00
Elementary	3,238	0.01	0.09	0.00	1.00
English language ability (1=Yes)	4,206	0.85	0.36	0.00	1.00

Source: Author's estimation based on LFS 2017 & 2018

Mean regression analysis

Table 3 reports regression results on graduate wage differentials whi ch were corrected for selection bias by adopting the DMF estimation approach. The differentials were considered for both log hourly and monthly wages. Stream-specific gender wage differentials were examined in Models 3 & 4. Estimates related to selection bias terms are also reported in Table 3.

Table 3: Graduate wage differentials – Mean regression

	Model 1	Model 2	Model 3	Model 4
Independent Variable	Dependent Variable			
	Log hourly wage	Log monthly wage	Log hourly wage	Log monthly wage
Constant	4.473*** (0.365)	9.07*** (0.357)	4.559*** (0.304)	9.168*** (0.362)
Age	0.019 (0.015)	0.036** (0.013)	0.016 (0.012)	0.033** (0.013)
Age square	-0.0001 (0.0002)	-0.0003** (0.0001)	-0.0001 (0.0001)	-0.0003** (0.0001)
Gender (Male=1)	0.062*** (0.017)	0.147*** (0.021)	0.025 (0.025)	0.030 (0.022)
Law	(0.450*** (0.119)	0.562*** (0.129)	0.396*** (0.121)	0.480*** (0.124)
Management	0.280*** (0.033)	0.348*** (0.040)	0.166*** (0.051)	0.226*** (0.046)
Commerce	0.171*** (0.039)	0.238*** (0.037)	0.078** (0.039)	0.131*** (0.044)
Medicine	0.490*** (0.107)	0.811*** (0.227)	0.452*** (0.145)	0.764*** (0.154)
Agriculture	0.002 (0.061)	0.076* (0.053)	0.004 (0.090)	0.042 (0.101)
Science	0.075** (0.034)	0.119*** (0.039)	0.025 (0.047)	0.046 (0.047)
Indigenous Medicine	-0.156 (0.134)	0.159* (0.101)	-0.012 (0.136)	0.248* (0.147)
Engineering	0.388*** (0.052)	0.550*** (0.054)	0.367*** (0.132)	0.508*** (0.128)
Computer Science	0.154* (0.099)	0.269** (0.089)	0.173* (0.114)	0.218* (0.136)
Other	0.195*** (0.049)	0.284*** (0.045)	0.110** (0.054)	0.150** (0.061)

	Model 1	Model 2	Model 3	Model 4
Independent Variable	Dependent Variable			
	Log hourly wage	Log monthly wage	Log hourly wage	Log monthly wage
Male - Law	-	-	0.149 (0.177)	0.223 (0.156)
Male - Management	-	-	0.239*** (0.070)	0.254*** (0.057)
Male - Commerce	-	-	0.212*** (0.065)	0.252*** (0.065)
Male - Medicine	-	-	0.120 (0.116)	0.0156 (0.147)
Male - Agriculture	-	-	0.053 (0.107)	0.114 (0.103)
Male - Science	-	-	0.126** (0.053)	0.180** (0.056)
Male - Indigenous Medicine	-	-	-0.359 (0.236)	-0.195 (0.176)
Male - Engineering	-	-	0.079 (0.135)	0.124 (0.135)
Male - Computer Science	-	-	0.0007 (0.152)	0.117 (0.148)
Male - Other	-	-	0.183** (0.070)	0.284*** (0.080)
Postgraduate qualification	0.122*** (0.025)	0.117*** (0.029)	0.119*** (0.025)	0.116*** (0.026)
English Ability	0.074*** (0.024)	0.087*** (0.026)	0.077*** (0.022)	0.092*** (0.025)
Occupation Effect	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes
No of observation Multinomial model	4206	4206	4206	4206
Pseudo R2	0.236	0.235	0.235	0.235
Selection effect				
_m1 (employed)	-0.440 (0.542)	-0.596 (0.53)	-0.053 (0.598)	-0.688 (0.565)
_m2 (unemployed)	0.191 (0.555)	-0.024 (0.596)	0.129 (0.616)	-0.075 (0.0638)
_m3 (Inactive)	-0.362 (0.646)	-0.376 (0.663)	-0.520 (0.718)	-0.576 (0.692)

Note: Standard errors are reported in parentheses and *, **, and *** indicate the estimated coefficients are statistically significant at 10%, 5%, and 1% respectively.

The estimated results in Models 1 through 4 confirm the presence of statistically significant study-stream wage differentials in the labour market. In other words, graduates of most study streams receive relatively higher hourly or monthly wages compared to Arts graduates. According to Model 1, a Law, Medicine, or Engineering graduate earns an hourly wage rate that is 38-45 per cent higher than an Arts graduate who is identical in all other observable characteristics. Similarly, a Management, Commerce, or Science graduate earns an hourly wage rate higher than an identical Arts graduate. The difference in earning rates among these graduates is 28%, 17%, and 7%, respectively.

The empirical evidence suggests that there is a positive wage premium for Computer graduates over Arts graduates though the statistical evidence remains somewhat weaker. Compared to Arts graduates, monthly wage premiums enjoyed by graduates of most subject streams remain relatively higher than hourly wage premiums. For instance, a medical graduate receives around 81% higher monthly wages compared to an identical Arts graduate. Similarly, an engineering graduate earns a monthly wage rate 55 per cent higher than that of an identical Arts graduate. However, no significant wage differentials exist among graduates of Arts, Agriculture, and Indigenous Medicine concerning hourly wages (see Table 3). Nevertheless, some weak evidence exists to suggest that monthly wages earned by graduates in the fields of Agriculture and Indigenous Medicine are marginally higher than that of an identical Arts graduate.

Overall, according to Model 2, graduates who earn a degree in fields other than Arts tend to enjoy a positive wage premium over an identical Arts graduate. This positive wage premium may reflect several factors such as higher demand for non-Arts graduates in the labour market, oversupply of Arts graduates, limited job market skills among Arts graduates, and limited opportunities for Arts graduates to access well-paid jobs due to skill mismatch. However, it is important to note that there is a greater heterogeneity among Arts and Humanities graduates and it is important to unbundle them to examine whether certain subjects outperform others. Currently, the labour force survey neither collects data on degrees by individual subject specialization nor reports grades of the degrees obtained, i.e. first class, second upper, etc. Hence, it might be interesting to investigate the graduate wage differentials along the above dimensions for valuable policy implications on investment in higher education.

The study also examined whether the estimated wage differentials in different study streams vary according to gender. Gender wage differentials in the fields of study have implications for equality. The estimated results for log hourly and monthly wages are reported under Model 3 and 4 respectively in Table 3. Accordingly, male graduates from Management, Commerce, and Science study streams earn higher wages than female graduates who have followed the same study stream. For instance, a male Management graduate earns a wage rate that is 24-25% higher than a female graduate who is identical in all other observable characteristics (see Model 3 and 4 in Table 3). Gender wage discrimination does not exist in Medicine, Engineering, Computer Science, and Law study streams. A positive wage premium for males in Management and Commerce study streams could be because jobs in those fields may require long hours of work as well as travelling. Hence, males may be preferred over females for most jobs available for Management and Commerce graduates. Moreover, female Science graduates do not enjoy a wage premium over Arts graduates. Policymakers need to pay attention to promoting equality in the labour market by removing gender barriers that lead to gender wage discrimination in the labour market.

Among the other variables employed in the regression models, the estimated coefficients of postgraduate qualification, English proficiency, age, and age square are statistically significant in most models. The estimated coefficients are in line with theoretical expectations. For instance, a postgraduate qualification enhances the graduate wage rate by about 11 to 12% whereas English proficiency increases wages by about 7-9%. In recent years, the number of postgraduate candidates increased rapidly in Sri Lanka, partly because they could enhance their earnings capacities with such qualifications. Annual (local students) enrollments for postgraduate degrees increased from 6,334 in 2008 to 35,250 in 2020 in the higher educational institutions in Sri Lanka (UGC, 2010 and 2020).

Pursuing a postgraduate degree is one of the best options available for graduates whose first-degree-related wages remain relatively lower compared to high-wage earnings fields of study. With respect to log monthly wage regression models, estimated coefficients of both age and age square variables are statistically significant with theoretically expected signs, i.e. the estimated coefficient of age is positive while the estimated coefficient of the age-square is negative. Following the literature, age is employed as a proxy variable for labour market experience (Grave, 2012). Accordingly, there is a non-linear relationship between labour market experience and monthly wages. It is also found that occupations and industry also explain a part of the wage differentials among graduates in the labour market.

Quantile regression analysis

Table 4 reports results from quantile regression estimation. The study examined wage differentials at 0.25, 0.5, and 0.75 quantiles. A few observations could be made based on the estimated results. First, in most cases, wage differentials could be observed across study streams in the graduate wage distribution. Compared to the Arts study stream, hourly and/or monthly wages are higher in most of the other study streams. Second, those differentials are higher in the upper part of the wage distribution (0.75 quantile) compared to the lower part of the wage distribution (0.25 quantile). For instance, monthly wage differentials between Arts and Medicine study streams are 63% at 0.25 quantile while this figure is 114% at 0.75 quantile. Similarly, between Arts and Management study streams, monthly wage differentials are 14.5% and 46.8%, respectively, at 0.25 and 0.75 quantiles.

Third, the gender effect is not statistically significant in hourly wages. But male graduates earn a monthly wage premium over identical female graduates. This may suggest that male graduates work longer hours than their female counterparts. Returns to experience, captured by the age variable, decline when moving from the lower segment of the wage distribution to the upper segment. This may partly reflect the fact that relatively older graduates are stacked at the upper segment of the wage distribution. Finally, the returns to postgraduate qualification are higher for graduates who are in the upper segment of the wage distribution. For instance, a graduate with a postgraduate qualification at the lower segment of the wage distribution earns a monthly wage that is higher by around 5 per cent compared to an identical graduate without a postgraduate qualification. In contrast, a graduate with a postgraduate qualification, at the upper segment of the wage distribution, earns a monthly wage that is higher by around 15% compared to an identical graduate without a postgraduate qualification.

Table 4: Graduate wage differentials - Quantile regression

	Log hourly wages			Log monthly wage		
	q25	q50	q75	q25	q50	q75
Constant	3.379***	4.378***	4.850***	8.392***	9.367***	9.783***
	(0.207)	(0.213)	-0.194	(0.277)	(0.228)	(0.187)
Age	0.059***	0.025***	0.009	0.059***	0.033***	0.021**
	(0.007)	(0.008)	-0.007	(0.010)	(0.007)	(0.008)
Age square	-0.0005***	-0.0001*	0.00004	-0.0006***	-0.0003***	-0.0001
	(0.0001)	(0.0001)	(0.00004)	(0.0001)	(0.0001)	(0.0001)
Gender (Male =1)	0.0001	0.007	0.027	0.037***	0.040***	0.103***
	(0.017)	(0.011)	(0.019)	(0.010)	(0.010)	(0.023)
Law	0.178***	0.417***	0.773***	0.215***	0.461***	0.730***
	(0.055)	(0.097)	(0.109)	(0.082)	(0.092)	(0.111)
Management	0.154***	0.165***	0.333***	0.145***	0.226***	0.468***
	(0.028)	(0.032)	(0.051)	(0.025)	(0.026)	(0.040)
Commerce	0.081***	0.115***	0.255***	0.073***	0.120***	0.340***
	(0.018)	(0.022)	(0.042)	(0.026)	(0.043)	(0.045)
Medicine	0.389***	0.574***	0.767***	0.634***	0.927***	1.145***
	(0.082)	(0.062)	(0.061)	(0.086)	(0.064)	(0.049)
Agriculture	-0.018	-0.007	0.040	0.085***	0.036	0.020
	(0.041)	(0.067)	(0.087)	(0.032)	(0.025)	(0.070)
Science	0.067***	0.075***	0.117***	0.075***	0.067***	0.191***
	(0.022)	(0.018)	(0.041)	(0.019)	(0.020)	(0.061)
Indigenous Medicine	-0.331**	-0.163	0.102	0.008	0.187**	0.366***
	(0.157)	(0.114)	(0.117)	(0.111)	(0.073)	(0.098)
Engineering	0.291***	0.390***	0.506***	0.469***	0.600***	0.761***
	(0.035)	(0.048)	(0.075)	(0.049)	(0.040)	(0.077)
Computer Science	0.119	0.104	0.181	0.153***	0.082	0.368*
	(0.096)	(0.098)	(0.185)	(0.043)	(0.115)	(0.188)

	Log hourly wages			Log monthly wage		
	q25	q50	q75	q25	q50	q75
Other	0.065**	0.085**	0.348***	0.107***	0.197***	0.497***
	(0.027)	(0.038)	(0.077)	(0.026)	(0.035)	(0.083)
Postgraduate qualification	0.066***	0.066***	0.133***	0.050***	0.046***	0.154***
	(0.019)	(0.012)	(0.025)	(0.019)	(0.015)	(0.030)
English Ability	0.033*	0.023	0.029**	0.029**	0.030***	0.021*
	(0.017)	(0.018)	(0.012)	(0.013)	(0.009)	(0.011)
Occupation Effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.13	0.22	0.31	0.12	0.18	0.24
No of observation	3,161	3,161	3,161	3,161	3,161	3,161

Conclusion

Aspirants of higher education and their parents often face a dilemma over the selection of a study stream that provides them with better employment and earning outcomes in the job market. Similarly, policymakers wish to channel limited public finances into study areas that provide better employment and earning opportunities for graduates. In such a context, returns to different study streams play a key role in informing interested parties to make rational choices. Nevertheless, the literature available on this aspect is limited in developing countries. In particular, limited studies in the context of Sri Lanka warrants further research to investigate the graduate wage differentials. This study investigated the graduate wage differentials by study stream based on data from the LFS, a nationally representative survey conducted and disseminated by the Department of Census and Statistics of Sri Lanka. It examined the data employing both mean and quantile regression approaches. Mean estimation was corrected for the sample selection bias and wage differentials were examined at three quantiles in the wage distribution.

Our findings strongly suggest the presence of statistically significant wage differentials among selected subject streams. Specifically, compared to the Arts study stream, most other study streams return higher earnings (hourly and monthly) in the labour market. In particular, Medical, Engineering, and Law graduates enjoy statistically significant positive wage premiums compared to graduates of Arts. Similarly, Management, Commerce, and Law graduates also earn a statistically significant positive wage premium over graduates of Arts. Statistical evidence suggesting that General Science and Computer Science graduates earn higher than Arts graduates is relatively weak. Nevertheless, Agriculture and Indigenous Medicine graduates do not enjoy a significant wage premium over Arts graduates. Both descriptive and regression analyses indicate that wage differentials among Arts, Agriculture, and Science graduates are either absent or very weak. This may imply that those graduates hold jobs that require a similar set of skills. In particular, the results provide some evidence to suggest that jobs traditionally held by Arts graduates are now allocated among graduates of the abovementioned fields of study. In that respect, wage differentials may not be a prime consideration that guides the students to select among the three fields of study but the probability to employed upon the completion of the degree.

Furthermore, wage differentials are relatively higher in the upper segment of the graduate wage distribution compared to the lower segment. In other words, graduates who have followed STEM study streams, Management, Commerce, and Law study streams earn much higher returns, compared to Arts graduates if they are in the upper segment of the wage distribution. This implies that the majority of those degree holders are in the upper segment of the wage distribution compared to the Arts graduates. Hence, wage inequality among graduates is partly due to differentials concerning the returns to the skill sets obtained in tertiary education.

Moreover, male graduates enjoy better returns compared to their female counterparts in study streams such as Management, Commerce, and Science. This means that there is a statistically significant gender wage gap in these fields. Nevertheless, the gender wage gap is not significant in study streams such as Engineering, Medicine, Law, and Computer Science.

Our findings indicate that the Medical, Engineering, Management, Commerce, and Law fields of study offer higher returns in the job market compared to the Arts study stream. However, further investigations are required to ascertain whether the returns justify the investments, in financial and non-financial terms, undertaken in pursuing those study streams compared to the Arts study stream. In the light of the above findings, one of the future research directions is to investigate the net returns to study streams.

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