EDUCATION

PIDE Working Papers
No. 2023:6

Pakistan Institute of Development Economics

Is the Decision to Obtain Higher Education in Pakistan Worth Repaying? New Evidence from Returns on Education for Paid-Employees

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Designed, composed, and finished at the Publications Division, PIDE.

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PAKISTAN INSTITUTE OF DEVELOPMENT ECONOMICS
ISLAMABAD
2023

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ABSTRACT

The labour market in Pakistan has failed to absorb the labour force who have obtained degrees of higher education due to skill mismatch, over-supply of labour who have higher education, and low quality of higher education. In such context, a question arises whether a household's decision to go for higher education is worth repaying or not. Therefore, the key objective of this research is to explore the returns on higher education that are declining relative to lower education in Pakistan. Moreover, the study has attempted to measure the non-linear relationship between schooling years and monthly wage. For the empirical purpose, all available rounds of Pakistan Social & Living Standard Measurement Survey (PSLM) datasets are employed. The Mincerian wage equation is estimated by applying Inverse Probability Weighting Regression AdJustment (IPWRA) and Instrumental Variable (IV) approaches to estimate said objectives. The findings obtained from IPWRA indicate that returns on higher education without professional degrees relative to the lower levels are falling at an increasing pace after 2010-11. Nonetheless, returns on professional degrees are increasing as compared to lower education. Similarly, IV results establish the non-linear relationship between schooling years, which demonstrate that after 2010-11, 12 years to 14 years of education is the optimum level. After these levels, returns on schooling years are falling. These striking results suggest that the government needs to focus more on promoting skills and development programs to enhance labour skills and the quality of education.

1. INTRODUCTION

Recent literature has been showing the decreasing returns on education against the huge amount of literature (Mamani-Choque, 2020; Psacharopoulos & Patrinos, 2018; Vecernik, 2013; Colclough, et al. 2010; Flabbi, et al. 2008; Fleisher, et al. 2005) which have suggested the increasing returns on education in developing countries. Doan, et al. (2018) have revealed that emerging economies are witnessing declining returns on education due to an over-supply of the educated labour force, skill mismatch, and changing structure and requirements of the labour market in these economies (Xie, 2020; Nieto & Ramos, 2017), while another strand of literature has argued the increasing returns on education due to the positive externalities of human capital. These positive externalities come by increasing the expenditures on research and development (R&D), knowledge creation through technological advancement, and enhancing the emerging skill requirement of the labour force is expected to expand the potential of workers which will result in increasing the returns on higher education owing to increase in the marginal productivity of the labour (Romer, 1990 & 1993). On contrary, workers with low adaptive and innovative capabilities are failed to learn quickly the usage of new technology due to poor skill development systems in their countries (ILO, 2015; Dicken, et al. 2006).

Pakistan is among those countries whose labour market is failed to produce decent jobs for its labour force. According to the Government of Pakistan (2018-19)[1], out of the total unemployed labour force, 78 percent are educated people, while 22 percent people are uneducated. On one side there is a huge rate of unemployment among educated people, especially among highly educated people who are facing a 20 percent unemployment rate. On the other hand, during the last couple of decades, enrollment in tertiary education is increasing overwhelmingly, new universities are being established without the provision of well-qualified teaching faculty and highly skilled human resource to provide enough infrastructure in universities, and poorly designed incentive structures which are only producing several degree holders without equipping of market-based skills. Moreover, the design of the Pakistani labour market is not conducive to people having degrees of higher education (ILO, 2016). In nutshell, the education system of Pakistan has failed to produce quality human capital as World Bank (2018) has shown that Pakistan stands to hold the 134th position out of 142 countries on the quality of the human capital index. The learning outcome gap is found at 4.8 years which demonstrates that the human capital of the country is extremely poor. Similarly, Kemal (2005) has suggested that negligence of enhancement in human resources and insufficient measures to improve skill development is the main reason behind the low human development index. Another study conducted by Maclean, et al. (2013) has revealed that after Mongolia, Pakistan contains the second-lowest share of the total students enrolled in technical and vocational education and training.

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[1]http://www.pbs.gov.pk/content/labour-force-statistics

In the light of above discussion regarding Pakistan, returns on higher education are expected to be more declining than lower education during the last decade. Nonetheless, the existing literature related to returns on education has shown increasing marginal returns on schooling years (e.g., Nazar & Chaudhry, 2017; Jaffry, et al. 2007; Nazli, 2004; Nasir & Nazli, 2000). On other hand, some researchers demonstrated that skill differential and over-supply of unskilled labour bring about wage differential which ultimately translates into lower returns for low-skilled workers (Pan, et al. 2019; Doan, et al. 2018). Apart from labour market factors for workers, some other socioeconomic characteristics are also very important to determine workers' returns. Such factors include parental education, income class of the workers, parental occupation, and location are the other important elements which are required to be considered as instruments of the decision to get higher education. The available literature regarding Pakistan is missing these instruments and some other methodological aspects which could change the outcome of the research. Hence, the ongoing study has endeavored to overcome the limitations of the existing literature along with updating the available data on households' socioeconomic characteristics and labour market indicators. In addition, the main hypothesis of the study returns on higher education are declining due to an over-supply of labour and skill mismatch with labour market requirements.

The specific research objectives of the underlying research are outlined as follows.

- To estimate whether the decision to pursue higher education relative to lower education is providing increasing returns or declining for paid-employee by using Inverse Probability Weighting Regression Adjustment (IPWRA)
- Exploring the non-linear relationship between schooling years and monthly wage earned by paid-employee
- Measuring the optimum level of education which maximises the monthly returns.

The subsequent part of the study is given as follows: Section 2 comprises data and variable description, while the methodological framework is described in Section 3. The results and discussion is hatched in Section 4, whereas the conclusion of the whole study is described in Section 5.

2. DATA SOURCE AND VARIABLE DESCRIPTION

To collect data on required variables, this paper employs all available rounds of the Pakistan Social & Living Standard Measurement Survey (PSLM) which is conducted by the Pakistan Bureau of Statistics (PBS)[2] during 2004-05, 2006-07, 2008-09, 2010-11, 2012-13, 2014-15, and 2019-20 to pluck the information of paid-employee (salaried class) to estimate the returns on their educational qualifications. PSLM provides more required information about family environment-related variables and district representative sample which would cover district-level impact as well.[3] The summary of the sample size of all surveys is presented in Table 1.

[2]http://www.pbs.gov.pk/content/pakistan-social-and-living-standards-measurement

[3]Alternatively, Most of the available literature regarding Pakistan has employed Labour Force Survey (LFS) to estimate returns on education. Limitations involved with LFS are that it is not a district representative, and it does not provide identification of workers' parents and household income as well. Parental variables are to use as instrumental variables in the study which will be discussed in the model specification.

Table 1

Summary of Sample Size

Survey Year	Total Households	Total Individuals	Paid Worker
PSLM 2004-05	73,410	500,660	56,258
PSLM 2006-07	73,953	496,060	58,166
PSLM 2008-09	75,773	499,739	57,780
PSLM 2010-11	76,548	499,215	61,813
PSLM 2012-13	75,516	492,632	59,311
PSLM 2014-15	78,635	513,099	56,120
PSLM 2019-20	160,654	870,171	109,705

Source: Pakistan Bureau of Statistics (PBS).

Literature on measuring returns earned from education educational qualifications has employed a log of monthly wage earnings (e.g., Khan & Khan, 2020; Nazli, 2004; Nasir & Nazli, 2000). Therefore, the ongoing research has employed the same definition, and educational qualification is measured through years of schooling and different levels of education. A brief description of the variables is given in Table 2.

Table 2

Summary of Variable Description

Variable Name	Description of Variables	Unit
Dependent Variable		
Outcome Variable		
Log Monthly Wage	Log of monthly income earned by paid-employee	PKR
Independent Variables		
Educational Variables		
Treatment Variable		
Higher education	The binary variable takes the value 1 if workers have BS/MA and MPhil/Ph.D. degrees without professionals, 0 otherwise	Binary
Control Group		Binary
Only Professionals	The binary variable takes the value 1 if workers have any of professional degrees such as medical, lawyers, accountant, etc., 0 otherwise	Binary
Under Metric	The binary variable takes the value 1 if workers have any of education below metric, 0 otherwise	Binary
Secondary	The binary variable takes the value 1 if workers have any of metric or intermediate education, 0 otherwise	Binary
Years of Schooling	Completed years of schooling of workers	Years
Square of Schooling Years	A square of years of schooling is used to estimate the non-linear impact of years of schooling on the outcome variable	Years
Schooling Square	Taking a square of years of schooling	Years
Other Variables		
Experience	Experience is measured by subtracting schooling years-6 years from the worker's age	Years
Experience Square	Taking square of experience to estimate non-linearity	Years
Gender of Worker	Takes value 1 if the gender of the worker is male, otherwise zero	Binary
Employment Sectors	The binary variable is constructed for each employment sector of workers such as agriculture, industrial, and services	Binary
Log of Household Income	Log of household monthly income earned by all household members	PKR
Parental Education	The variable takes the value 1 if the parents of the worker are educated, otherwise zero for no education	Binary
Father Occupations	Binary variables of elementary, crafts, and sale worker are computed separately	Binary
Region	The variable takes value=1 if the region of the worker is rural, and zero for the urban area	Binary

Note: Variables are constructed by the author from all rounds of PSLM datasets.

3. EMPIRICAL STRATEGY

An excess of literature has been using Mincer's (1974) model[4] to estimate marginal returns on education (e.g., Doan, et al. 2018; Nazar & Chaudhry, 2017; Nieto & Ramos, 2017; Jamal (2015); Vecernik, 2013; Flabbi, et al. 2008; Jaffry, et al. 2007; Fleisher, et al. 2005; Nazli, 2004; Nasir & Nazli, 2000). The standard Mincerian equation specifies the log of monthly wages on estimating the impacts of years of schooling and experience of workers. As the objective is to measure the returns on higher education without professional degrees relative to lower levels of education, the specification of the Mincerian wage equation is given as follows.

$$Lny_i = \alpha_o + B_1 Ed_i + B_2 Exp._i + B_3 (Exp.)_i^2 + B_4 Gender_i + B_5 sector_i + B_6 region_i + \varepsilon_i \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (1)$$

In the above equation, Lny_i is the log of the monthly wage, Ed_i indicates a binary variable for higher education without professionals where professional degrees, only professional degrees, secondary education, and under metric are reference groups. In addition, Exp. shows the experience of the worker, and sector denotes employment sectors such as agriculture, industrial, and services sector, while region shows the locality of the job whether in rural areas or urban. Simple OLS estimation would give the bias results due to the decision of the household whether he or she should go for higher education or not. Households' decision to go for higher education is endogenous, and it brings about non-randomness, which would give biased results if it is not tackled (e.g., Heckman, 1976). To my knowledge, most of the studies have used the OLS estimator to estimate Equation (1), which could give the bias results. To obtain unbiased and robust analysis, there needs to apply Hecket models[5]. As the study aims to estimate the causal impacts of the household's decision to pursue higher education such as Master/BS, and MPhil/Ph.D., etc. or stopped studying further on their wage earnings, the literature suggests multiple empirical strategies such as endogenous switching regression model, propensity score matching, and treatment effect models with selection bias (e.g., Mustafa et al. 2021; Ahmed, et al. 2016). This study employs types of treatment effect models such as Inverse Probability Weighting Regression Adjustment (IPWRA) to estimate the Equation (1), when a household member's decision is endogenous as applied by Ahmed, et al. (2016). IPWRA follows a two-step process of estimation, where the second stage is measuring the outcome equation which is Equation (1). Nonetheless, before the estimation of the outcome equation, the first stage is the estimation of the treatment equation is required to be implemented, which has the following specification.

$$t_i^* = \gamma'_i Z + v_i \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (2)$$

In Equation (2), t_i is a treatment variable such as 1= higher education without professional degrees, professional degrees=2, secondary education=3, below-metric=4, while 0 for other levels of education. Z is a vector of variables that influence the

[4]This model is known as *the Mincerian wage equation* or *the Mincerian human capital model.*

[5]Heckman (1976) has suggested a sample-selection model which is a two-step model. After that, several extensions have been introduced to find out the causal impacts when there is a selection bias as well in the model.

household's decision to pursue higher education or not like worker gender, monthly family income, parental education, father's occupation, and location (rural or urban). These factors play an important role to determine a household's decision to move further for higher education or not. Equation (2) looks like Logit/Probit estimation. In the second stage, Equation (1) is estimated separately for both those who obtained higher education and those who did not obtain higher education. Moreover, treatment Equation (2) could be multinomial as well, when the setting of treatment could be like higher education without professional, only professional degrees, secondary, and under metric education levels. In this case, the outcome equation is estimated separately for each category except the reference group.

IPWRA is a combination of the two treatment effect approaches Inverse Probability Weighting (IPW) and Regression Adjustment (RA), where IPW estimates the weights at the first stage by applying the Logit/Probit estimation technique based on given variables, after that inverse of those estimated weights is imputed with outcome equations which provides the robust estimates. Likewise, RA is the regression modeling of the outcome variable (log of wage) to fix the missing variable problem in treatment effect estimation. This method uses the averages of the predicted outcomes to estimate potential outcomes means an average treatment effect, which provides robust estimates. Hence, the amalgamation of IPW and RA is considered the most appropriate specification to measure the potential outcome mean (POM) and treatment effect (Ahmed, et al. 2016; Cameron & Trivedi, 2005). The average treatment effect (ATE) is estimated by taking the difference between the POM of the treatment group and the POM of the control group (reference group), the specification of ATE is weaved up as follows.

$$\text{ATE}= \text{E}\ (LnY_{1\,i}\,|(t_i = 1) - \text{E}\ (LnY_{0\,i}\,|(t_i = 0) \qquad \dots \qquad \dots \qquad \dots \qquad (3)$$

The above equation explains the formula which provides an estimation of the average treatment effect (ATE), where the treatment group is in higher education, while the control group is at other levels of education. IPWRA could provide the POM for each level of education, and by using the method given by Equation (3) would estimate the ATE for desired groups.

In addition to the causal relationship between higher education relative to other education levels and the log of the monthly wage, the underlying research aims to estimate the non-linear relationship of the schooling years which would also provide another method to estimate whether the decision to obtain higher education is worth having or not. If the non-linear term of schooling years is negative and statistically significant, while the linear term is positive, this study would conclude that there could be an 'inverted U-shaped' relationship between years of schooling and the log of monthly wage earnings. A threshold through maximisation of the wage function, we would come to know what level of years of schooling is maximising the worker's monthly earnings. For this purpose, the Equation (1) forms the following specification as Doan, et al. (2018) for Vietnam have specified.

$$\begin{aligned} Lny_i = \alpha_o + B_1 S_i + B_2 (S)_i^2 + B_3 Exp._i + B_4 (Exp.)_i^2 + B_5 Gender_i \\ + B_6 sector_i + B_7 region_i + \varepsilon_i \qquad \dots \qquad \dots \qquad \dots \qquad \dots \qquad (5) \end{aligned}$$

Here, S denotes the schooling years of individual i, S^2 uses to capture a non-linear pattern in the lifecycle schooling of individual i. The specified model is estimated by using the

Instrumental Variable (IV) approach because years of schooling are endogenous and depend upon parental education, family income, occupation of the father, and region of workers[6] (Blundell, et al. 2001). Although I have applied some instrument validity tests which show no serious concerns about the instrument, still household family environment is hard to be theoretically exogenous.

4. RESULTS AND DISCUSSION

This section is furnished with results and discussion from twofold empirical strategies: (i) analysis of average treatment effect and potential outcome means for different education levels estimated by the implementation of Inverse-Weighting Probability Regression Adjustment (IWP-RA), and (ii) estimation of the non-linear relationship between years of schooling and monthly wage earnings through Instrumental Variable (IV) approach. The detailed discussion on results obtained from the aforementioned methods is hatched up as follows.

4.1. Estimation of Returns on Higher Education: Average Treatment Effect (ATE) Analysis

As the objective of the study is to estimate monthly returns on higher education relative to the lower levels of education, the application of IPWRA provides us with potential outcome means an average treatment effect (ATE) for under matriculation, secondary education, and higher education without professionals, and only professional degrees. The outcome variable is a log of monthly income while the treatment group is higher education without professional degrees, while the rest of the educational categories are fixed as the control group. The study has estimated separate models for each round of the PSLM from 2004-05 to the most recent round 2019-20 respectively. Table 3 comprises the description of the results of ATEs, while the results of outcome equations for control variables and treatment equations are presented in the appendix.

Estimated results indicate that the potential outcome means (POM) of the treatment group (higher education without professional degrees) is estimated at 8.38 percent with positive sign and statistically significant during 2004-05, control groups such as those below metric education (8.03 percent), secondary education (8.21 percent), and professional degrees (8.35 percent). These estimates reveal that there is no colossal difference between the treatment group and control groups during 2004-05. The difference between these is called ATE, which is positive and statistically significant. Such findings showcase that there is almost less than one percent difference between higher education without professionals relative to control groups (Table 3). Nonetheless, in the analysis of ATE, the positivity of the coefficients also carry its weight. It becomes evident that during 2004-05, workers with higher education such as MSc./MA, MPhil, and PhDs, etc. are yielding relatively higher monthly returns as compared to lower education groups (below metric, and secondary education), while insignificant ATE, but with the positive coefficient for higher education relative to professional degrees construes that there is no significant difference in monthly returns for these two groups during 2004-05 (Table 3).

[6]Household-specific characteristics are not as exogenous as we need an exogenous variable as an instrument. Nonetheless, no dearth of literature takes them as important factors which influence the household's decision to go for education (e.g.; Heckman, 1976; Ahmed, et al. 2016).

The estimated POM for higher education without professionals takes a slight increment during 2006-07, which is estimated at 8.70, whereas workers with professional degrees experience a slightly higher POM of 8.89. The ATE (–0.1974) is estimated negatively but statistically significant, which implies that workers who have higher education without professionals relative to workers having professional degrees are experiencing a decline in returns during 2006-07. Nonetheless, ATEs for higher education relative to the lower education group are positive and significant, although the difference is not much wider. Such results unleash that higher education relative to the lower education groups (below metric and secondary) are experiencing relatively increasing returns during 2006-07. Likewise, the trend of the monthly returns on higher education is increasing relative to the lower education, while lower returns relative to the workers who have professional degrees during 2008-09 and 2010-11 (see, Table 3).

Table 3

Estimated Returns on Higher Education Relative to Lower Level of Education in Pakistan

	(%) Potential Outcome Means (PoMs)				(%) Average Treatment Effect (ATE)		
	Multivariate Treatments				Difference between PoM of treatment and control groups		
	(1)	(2)	(3)	(4)			
PSLM Rounds	Higher Education	Professional Degrees	Secondary	Below Matric	ATE= (1)-(2)	ATE= (1)-(3)	ATE= (1)-(4)
PSLM 2004-05	8.3868***	8.3543***	8.2191***	8.034***	0.0324	0.167***	0.352***
	(0.029)	(0.104)	(0.009)	(0.007)	(0.108)	(0.030)	(0.031)
PSLM 2006-07	8.7023***	8.8998***	8.5143***	8.319***	–0.197***	0.188***	0.382***
	(0.027)	(0.056)	(0.008)	(0.011)	(0.062)	(0.027)	(0.012)
PSLM 2008-09	8.9281***	9.0935***	8.7742***	8.548***	–0.165***	0 .153***	0.379***
	(0.018)	(0.045)	(0.006)	(0.008)	(0.048)	(0.018)	(0.020)
PSLM 2010-11	9.4057***	9.7332***	9.2774***	9.074***	–0.327***	0.128***	0.331***
	(0.029)	(0.005)	(0.006)	(0.011)	(0.112)	(0.030)	(0.031)
PSLM 2012-13	9.0440***	9.7308***	9.2657***	9.009***	–0.6868***	–0.221***	0.034***
	(0.028)	(0.079)	(0.006)	(0.015)	(0.028)	(0.017)	(0.032)
PSLM 2014-15	8. 3658***	9.7880***	9.3088***	9.444***	–1.422***	–0.943**	–1.078**
	(0.024)	(0.089)	(0.006)	(0.013)	(0.099)	(0.153)	(0.124)
PSLM 2019-20	7. 0019***	10.2478***	9.8703***	9.692***	–3.245***	–2.868***	–2.690***
	(0.011)	(0.066)	(0.004)	(0.012)	(0.477)	(1.739)	(1.739)

Note: (a): These estimates are obtained by implementing the Inverse-Probability Weighting Regression Adjustment (IPW-RA) method to compute the potential outcome means (POMs) for each education level. Average treatment effects (ATE) are calculated by subtracting the PoMs of lower levels of education and education of professional degrees from the higher level of education. Statistically significant positive signs of the ATEs indicate higher education relative to the lower levels has higher (%) monthly returns. The smaller values of both PoMs and ATEs over time would showcase the declining trend of the returns. Results in this table demonstrate that on average, returns on higher education relative to the lower levels and professionals are showing a declining trend with an increasing rate after 2010-11.

(b) ATE=(1)-(2) indicates average treatment effect for higher education versus professionals, ATE=(1)-(3) shows average treatment effect for higher education versus secondary education, and ATE=(1)-(4) presents average treatment effect for higher education versus below metric

(c) Values presented in parenthesis are household-adjusted robust standard errors, and *** p<0.01, ** p<0.05, and * p<0.1.

Unlike previous years, returns on higher education without professionals relative to both lower education groups and only professionals started declining during 2012-13. The POM for higher education is estimated at 9.0440, while the coefficient of ATE for higher education relative to secondary education comes out with a negative sign, which exhibits that workers with degrees of intermediate, and matriculation are yielding relatively higher monthly returns as compared to the higher education without professional degrees. In addition, the ATE for higher education relative to below-metric education is still positive and statistically significant, but the magnitude is a bit smaller than in previous years, which also demonstrates that returns in relative terms have declined for higher education as compared to below-metric during 2012-13. This decline in returns continues increasingly after that. POM for higher education without professionals is estimated at 8.36 and 7.0019 during 2014-15 and 2019-20 respectively (see, Table 3). Moreover, the ATEs for higher education relative to both professionals (–1 percent to 3 percent) and lower education (–1 percent to 2 percent) significantly declined at an increasing rate after 2012-13. The highest decline in returns on higher education has been observed during 2019-20.

The underlying study also has estimated the results by including the category of illiterate in the model (see table-7 in the appendix). The findings demonstrate no significant difference as compared to the results given in Table 3.

Findings received from ATEs and POMs analysis can be concluded that marginal returns on higher education without professional degrees relative to those lower educational groups such as those under metric, and secondary education are declining trends in returns on education since 2010-11. Likewise, higher education without professionals relative to those who have professional degrees such as medicine, lawyers, accountants, and IT specialists are earning higher returns. Moreover, I have computed the mean of monthly wage without any regression (see, Table 6 in the Appendix), the findings also suggest a more or less similar sort of trend as we have found from IPWRA.

4.2. Non-linear Relationship between Schooling Years and Monthly Wage: IV Approach

To obtain more robust evidence to substantiate previously discussed findings, we have applied the instrumental variable (IV) approach by estimating the models for schooling years instead of education levels. The paramount objective is to locate what is the optimum level of education which maximises the returns. For this purpose, the square term of the schooling years is included in the model along with the linear term. Years of schooling are instrumented by household monthly income, parental education, parental occupation, and location (rural or urban). The diagnostic tests to estimate the validity of the instruments are found non-problematic.

Results obtained from the IV approach are demonstrative that the linear term of years of schooling is found positive and statistically significant during 2004-05, while its non-linear term (square term of years of schooling) is containing negative and statistically significant (see, Table 4). The linear term demonstrates that other things remain the same, with the increase of years of schooling yields increase in monthly returns by 26 percent, while the non-linear term shows a virtually zero percent decline in returns. The statistical significance of the square term or non-linear term shows an 'Inverted U-shaped' relationship between years of schooling and monthly log wages. This explains that initially there is an increment in returns with an increasing year of schooling, nonetheless, after a certain level, there is a slight decline in returns which is approximately less than one percent. We have estimated what is the optimum level of threshold of the year of schooling which maximises the returns on education. Through the simple mathematical tool of optimisation such as first-order condition, we have estimated approximately 24 years is the optimum level of years of schooling which maximises the worker's monthly returns on education. The estimation of 24 years of schooling demonstrates that higher education such as Ph.D. and Mphil etc. is one of the significant sources of maximising monthly earnings. Hence, these findings conclude that during 2004-05, workers who have Ph.D. degrees are found to experience the highest returns on their decision to pursue higher-level education. Similarly, during 2006-07, the marginal impacts of schooling variables on monthly wage income come out higher for higher education. Likewise, last findings, returns on years of schooling remain consistent and witness trivial change. The optimum level of years of schooling has been estimated as 22 years, which is almost equivalent to Ph.D. and MPhil degrees. Therefore, we may conclude that during 2004-05 to 2006-07, the returns on higher education are estimated as the highest (see, Table 4).

Table 4

Estimation of Non-Linear Impacts of Years of Schooling on Log of Wage from IV Approach

	2004-05	2006-07	2008-09	2010-11	2012-13	2014-15	2019-20
Schooling (years)	0.2623***	0.2621***	0.0014	0.850***	0.339***	0.882***	0.326***
	(0.038)	(0.019)	(0.183)	(0.021)	(0.024)	(0.059)	(0.015)
Non-linear	–0.0052**	–0.0060***	–0.0154	–0.0312***	–0.0114***	–0.0389***	–0.0115***
Term	(0.002)	(0.001)	(0.012)	(0.001)	(0.001)	(0.004)	(0.0008)
Threshold	24 years	22 years	N/A	13 years	14 years	12 years	14 years
Gender (=M)	0.486***	0.582***	0.777***	1.326***	0.519***	0.174***	–0.479***
	(0.034)	(0.021)	(0.125)	(0.029)	(0.023)	(0.045)	(0.017)
Experience	0.0386***	0.0351***	0.0152***	0.125***	0.0445***	0.0474***	0.0300***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.0009)
Non-linear	–0.0004**	–0.0003***	–2.60e-05	–0.0019***	–0.0004***	–0.0003***	–0.0002***
Term	(3.67e-05)	(2.59e-05)	(4.75e-05)	(5.28e-05)	(2.69e-05)	(4.42e-05)	(1.94e-05)
Industrial	0.175***	0.0212	0.0886	0.490***	–0.113***	–0.438***	–0.101***
	(0.040)	(0.022)	(0.108)	(0.020)	(0.022)	(0.041)	(0.016)
Services	–0.0948*	–0.268***	–0.312*	0.690***	-0.414***	–0.921***	–0.348***
	(0.049)	(0.027)	(0.164)	(0.022)	(0.029)	(0.059)	(0.022)
Area urban	–0.114***	–0.0976***	–0.162***	0.0797***	–0.126***	–0.215***	–0.0277***
	(0.021)	(0.011)	(0.016)	(0.013)	(0.012)	(0.023)	(0.007)
Constant	5.956***	6.329***	6.926***	6.257***	6.964***	6.884***	8.774***
	(0.045)	(0.029)	(0.167)	(0.042)	(0.027)	(0.047)	(0.038)
Observations	47,689	49,990	37,552	52,957	50,724	49,832	109,705

Note: (1) The results presented in this table are estimated by using the instrumental variable (IV) approach, where household income, parental occupation, and location of dwelling are taken as instruments for the schooling years' variable. The nonlinear term is included to obtain the threshold of education. The results demonstrate that after 2010-11 the returns on higher education are falling after around 13 to 14 years of schooling.

(2) Moreover, robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Unlike to above findings, the impacts of years of schooling on the log of monthly wages during 2008-09 are found statistically insignificant for both linear and non-linear terms. Due to the statistical insignificance of the coefficients, we failed to deduct any conclusive evidence about the non-linearity of the years of schooling, although in terms of sign the relationship appears to be 'Inverted U-shaped', but findings carry no statistical significance. The implication of this finding may showcase the prominent shift in the labour market in terms of returns on years of schooling in Pakistan because, from that, the marginal returns on higher levels of schooling years start falling. Findings from the IV approach for the years of 2010-11 suggest that the marginal effects of schooling years for the linear term are still positive and significant, but the coefficient of the non-linear term comes out negative and significant which is around 3 percent. Non-linearity of schooling years has reconfirmed the persistence of the 'Inverted U-shaped' relationship between years of schooling and the log of monthly wages during 2010-11. Such relationship continues to be prevailing for the subsequent years such as 2012-13, 2014-15, and 2019-20. From this estimation, the optimum level of the threshold for earning is also estimated, and we have found that after 2008-09, the optimum years of schooling have shown a significant decline from 22 years to the range of 12 to 14 years of schooling respectively. Such results suggest that those workers who have degrees of 12 to 14 years of schooling are experiencing a maximum level of wage earnings. Another implication of these results is that workers who have lower education are experiencing an increasing level of returns on education till 12 to 14 years of schooling. After these levels, the returns on education are declining as evident from the negative sign of the non-linear term of the schooling years for 2012-13 to 2019-20 (see, Table 4). These results are contrary to the existing literature regarding Pakistan (e.g. Nazar & Chaudhry, 2017; Jaffry, et al. 2007; Nazli, 2004; Nasir & Nazli, 2000). These studies have on average found increasing returns on years of schooling.

Moreover, the underlying study has estimated interaction regression to test whether returns decline since 2010-11 as suggested by Doan, et al. (2017). In this regard, PSLM 2010-11 is pooled with 2012-13, 2014-15, and 2019-20 respectively[7]. These pooled datasets are estimated by the IV approach. The negative and significant sign of the interacted variable of schooling with the second-year dummy variable would suggest that returns on education are falling as compared to the base year 2010-11 during respective years (see, Table 5).

The Estimated results again confirm the falling returns on education as the linear term of schooling education is showing marginal returns on education are declining after 2010-11. The coefficients for years of schooling during 2010-11 are found positive and significant impacts, while the interaction term of schooling years and second-time dummy variable is estimated as negative and significant in the specified three years as compared to the base period 2010-11. Hence, all these findings are demonstrating the

[7]The log of wage is estimated by pooling the PSLM for the years 2010-11, 2012-13, 2014-15, and 2019-20 from the application of the IV approach. Three combinations of pooled data are designed (2010-11 & 2012-13), (2010-11 & 2014-15), and (2010-11 & 2019-20). These are estimated separately and the interaction of years of schooling in 2010-11 with a year dummy of the next year is introduced for each combination. The negative and significant sign of this interaction term will indicate that returns on education are falling in the respective period as compared to 2010-11.

tests of declining returns on education since 2010-11. This trend of declining returns on education continues to decline till 2019-20 (see, Table 5). These results seem quite consistent with the findings of Doan, et al. (2018) for Vietnam.

Table 5

Test of Declining Returns on Schooling Years Since 2010-11: Interaction Regression

	2010-11/2012-13		2010-11/2014-15		2010-11/2019-20	
Variables	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Schooling Years (SY)	0.0951***	2.85	0.0712**	2.09	0.0211*	1.77
Interact SY and 2nd Year	–0.0875***	–2.77	–0.0885**	–2.82	–0.0363	–1.38
Schooling Square (SS)	0.0007	0.36	0.0022	0.99	0.0055***	3.01
Interact SS and 2nd Year	0.0050**	2.44	0.0064***	3.03	0.0021	1.19
Experience	0.0185***	13.81	0.0176***	12.26	0.0158***	12.85
Interact Exper. 2nd Year	0.0521***	35.69	0.0424***	25.68	0.0391***	19.98
Experience Square (ES)	–0.0009***	–41.83	–0.0007***	–34.77	–0.0007***	–26.14
Interact ES.2nd Year	–0.0005***	–7.66	2.5E-05	0.29	0.0003***	3.79
Worker Gender	0.6687***	14.67	0.6887***	13.85	0.7303***	14.63
Interact Gender.2nd Year	-0.0110	–0.16	0.1136*	1.69	0.1001	1.58
Region (1=Rural)	–0.0654***	–3.18	–0.0677***	–3.41	–0.0727***	–3.58
Interact Region.2nd Year	–0.1379***	–4.25	–0.0350	–1.18	0.1342***	4.77
_cons	7.0779***	99.39	7.1264***	117.8	7.2277***	182.58
F-statistic	1318.41***		1057.85***		945.17***	
R-Squared	0.4266		0.4994		0.4962	

Note: *, **, *** indicates significance level at p<0.1, p<0.05, and p<0.001 respectively. Second-year dummy= takes the value 1 for the second year and zero for the base period 2010-11. And each variable has interacted with respective models. The findings showcase that the interactive term of schooling years of 2010-11 with a time dummy of next year is found significant and negative, which indicates that returns on overall schooling after 2010-11 are falling during 2012-13, 2014-15, and 2019-20.

As the primary aim of the ongoing research is to gather empirical evidence on declining returns on higher education in Pakistan. So far discussion has put stress on the core objective of the study. Nevertheless, control variables of the Mincerianequations such as experience, experience square, and interaction terms of experience and education, gender of worker, and location of the workers have shown statistically significant results in all estimations we have discussed so far—estimation by IPWRA and IV approach respectively.

By concluding the whole discussion we have hatched so far, the ongoing research has found that workers with higher education such as master/BS, MPhil, and PhDs are experiencing a decline in marginal returns, while the workers who lower education are witnessing a relatively lower level of decline in monthly marginal returns. Similarly, we have established that returns on years of schooling have an ‘Inverted U-shaped’ relationship with the log of monthly wage through the implementation of the instrumental variable (IV) approach. Further results substantiate that after 2008-09, from 12 years of workers schooling to 14 years of schooling is an optimum level of threshold that maximises the worker’s monthly marginal returns on education, while beyond these levels of schooling years, the decline in monthly marginal returns has been witnessed increasingly. This mentioned a decline in returns may be an outcome of three reasons such as over-supply of labour having higher education, skill-mismatch of the disposed of educated students, and unresponsiveness of the labour market due to its curtailing size.

5. CONCLUSION

The human capital of Pakistan faces major problems such as skill mismatch: such as people have degrees and education qualifications but they lack skills. Owing to skill shortage and non-responsive behaviour of the labour market to supply labour is causing a decline in returns on education in Pakistan during the last decade. The main concern of this paper is to estimate whether returns on higher education are falling or not. In this regard, all rounds of PSLM datasets are employed to investigate returns on education over time. Instrumental Variable (IV) and Inverse Probability Matching Regression Adjustment (IPWRA) are applied. Parental education, family income, and father occupations are the instruments that are used to achieve the specified objective of the study. Findings obtained by the IPWRA approach are suggestive of declining returns on higher education relative to lower education (secondary and under metric) since 2010-11, while professional degree holders such as medical doctors, engineers, and other professionals are found to earn the highest returns. These results have vital implications that the labour market of Pakistan is more structured to absorb the labour force with low education, and workers with professional and highly skillful degrees than individuals who have degrees of MPhil, PhDs, etc.

Similarly, results are found robust and consistent when the non-linear relationship between the log of wage and years of schooling is tested through the IV approach. Findings indicate that before 2008-09, higher levels of schooling years are found optimum to maximise the monthly marginal returns. Nonetheless, after 2008-09, the optimum level of education falls from 22 years to 12 to 14 years of schooling which maximises the individual's monthly wage earnings. In addition, interactive regression is estimated through the IV approach where the hypothesis is tested that since 2010-11 the returns on education are falling fastly. The results substantiate the previously discussed findings from IV and IPWRA approaches. This paper suggests some policy recommendations which include the government's need to more focus on promoting skills and development programs to enhance the skills of labour. Moreover, enhancing enrollment should not be the only priority, and policymakers must focus on the quality of education as well.

Appendix

Table 3a

Results Description of Outcome Equations from IPWRA Estimation

	Outcome Equation Results 2019-20				Outcome Equation Results 2014-15			
	OME-1	OME-2	OME-3	OME-4	OME-1	OME-2	OME-3	OME-4
Worker Gender	–0.7005	–0.3084	–0.3023	0.4038	0.6586	0.3593	0.5642	–0.5671
Experience	0.0493	0.0448	0.0526	0.0453	0.0519	0.0610	0.0791	0.0042
Experience Square	–0.0007	–0.0005	–0.0006	–0.0005	–0.0007	–0.0008	–0.0011	0.0005
Industrial Sector	0.2465	0.2837	0.3087	–0.3310	0.2059	0.2684	0.1590	0.4931
Services Sector	0.3371	0.4616	0.4605	–0.2196	0.2690	0.4551	0.4600	0.5513
Region_Urban	0.1441	0.1192	0.2129	0.3555	–0.0112	0.0371	0.1354	0.2511
_Cons	9.5092	9.1672	9.1587	9.3024	7.6743	7.8729	7.5545	9.4334

Note: All estimates are statistically significant.
OME-1= outcome equation for workers who have below metric education.
OME-2= outcome equation for workers who have secondary education.
OME-3 outcome equation for workers with higher education without professionals.
The OME-4=outcome equation for workers who have professional degrees.

Table 3b

Results of Treatment Equations from the IPWRA Approach

	Treatment Equations 2019-20			Treatment Equations 2014-15		
	TE-2	TE-3	TE-4	TE-2	TE-3	TE-4
Worker Gender	0.4901	2.1308	1.7280	–0.3853	–1.3209	–0.3387
HH Income Class						
First Quintile	reference	reference	reference	reference	reference	reference
Second Quintile	0.2909	0.0638	–0.3738	0.2518	0.3031	0.0265
Third Quintile	0.4788	0.7205	0.6282	0.3904	0.8420	0.5316
Fourth Quintile	0.7120	1.4875	2.0452	0.6315	1.5543	1.2101
Fifth Quintile	0.9379	2.4480	4.1342	1.0378	2.6042	3.8479
Dependency Ratio	–0.0982	0.0977	–0.0095	0.0245	0.0909	0.1408
Father Occupation_1	2.1095	2.3895	2.1160	0.7083	2.0542	2.7354
Father Occupation_2	1.2988	3.1427	3.6327	1.9403	3.8613	4.5667
Father Occupation_3	1.1677	2.0158	1.7083	1.2617	2.0681	2.8213
Father Occupation_4	1.6646	2.5415	1.5175	1.9329	3.0730	2.8389
KPK	0.1359	0.1974	0.3212	0.3459	0.7725	0.5326
Punjab	–0.3099	–0.5456	–0.2942	–0.2789	0.0250	0.0225
Sindh	0.2943	0.1639	0.3653	0.2324	0.7946	0.9128
Location (Urban)	0.2919	0.6239	1.2908	0.2631	0.6830	1.3983
_Cons	–1.2851	–5.3039	–9.1495	–0.8078	–3.1575	–8.4144

Note: All estimates are statistically significant. First four occupations of father professionals, technicians, etc.

TE-2= treatment equation for workers who have secondary education

TE-3= treatment equation for workers who have higher education without professional degrees

TE-4= treatment equation for workers who have professional degrees, while TE-1 is a reference group here for all treatment equations

Note: I have just reported here for only two latest years (2019-20 & 2014-15), Nonetheless such tables are produced for all available years.

Table 7

Estimated Returns on Education in Pakistan

	(%) Potential Outcome Means (PoMs) Multivariate Treatment Groups				(%) Average Treatment Effect (ATE) Difference between PoM of Treatment and Control Groups		
	(1)	(2)	(3)	(4)			
PSLM Rounds	Higher Education	Professional Degrees	Lower Education	Illiterate	ATE= (1)-(2)	ATE= (1)-(3)	ATE= (1)-(4)
PSLM 2004-05	8.3868***	8.3543***	8.2165***	7.861***	0.0324	0.173***	0.525***
	(0.029)	(0.104)	(0.009)	(0.007)	(0.108)	(0.030)	(0.031)
PSLM 2006-07	8.7023***	8.8998***	8.4166***	8.009***	–0.197***	0.288***	0.680***
	(0.027)	(0.056)	(0.008)	(0.011)	(0.062)	(0.027)	(0.012)
PSLM 2008-09	8.9281***	9.0935***	8.6611***	8.041***	–0.165***	0 .267***	0.887***
	(0.018)	(0.045)	(0.006)	(0.008)	(0.048)	(0.018)	(0.020)
PSLM 2010-11	9.4057***	9.7332***	9.1757***	8.154***	–0.327***	0.238***	1.25***
	(0.029)	(0.005)	(0.006)	(0.011)	(0.112)	(0.030)	(0.031)
PSLM 2012-13	9.0440***	9.7308***	9.3571***	8.091***	–0.6868***	–0.321***	0.953***
	(0.028)	(0.079)	(0.006)	(0.015)	(0.028)	(0.017)	(0.032)
PSLM 2014-15	8. 3658***	9.7880***	9.3880***	8.046***	–1.422***	-1.023**	0.319**
	(0.024)	(0.089)	(0.006)	(0.013)	(0.099)	(0.153)	(0.124)
PSLM 2019-20	7. 0019***	10.2478***	9.8721***	8.012***	–3.245***	–2.878***	–1.010***
	(0.011)	(0.066)	(0.004)	(0.012)	(0.477)	(1.739)	(1.739)

Note: (a): These estimates are obtained by implementing the Inverse-Probability Weighting Regression Adjustment (IPW-RA) method to compute the potential outcome means (POMs) for each education level. Average treatment effects (ATE) are calculated by subtracting the PoMs of lower levels of education and education of professional degrees from the higher level of education. Statistically significant positive signs of the ATEs indicate higher education relative to the lower levels has higher (%) monthly returns. The smaller values of both PoMs and ATEs over time would showcase the declining trend of the returns. Results in this table demonstrate that on average, returns on higher education relative to the lower levels and professionals are showing a declining trend with an increasing rate after 2010-11.

(b) Values presented in parenthesis are household-adjusted robust standard errors, and *** $p<0.01$, ** $p<0.05$, and * $p<0.1$.

Table 6

Mean Monthly Wage by Education Groups from All Rounds of PSLM

Education Groups	2004-05	2006-07	2008-09	2010-11	2012-13	2014-15	2019-20
Illiterate/Uneducated	2982.481	3698.317	4890.832	7224.52	7349.581	8028.389	14730.50
Below Metric	3390.445	4366.446	5703.196	8293.561	8560.348	10240.56	17580.87
Secondary	5092.103	6629.489	8232.199	13254.8	13636.94	15323.21	24426.31
Higher Education Without Professional Degrees	9860.117	12292.73	15389.62	24804.13	25592.66	31157.32	43598.89
Professional Degrees	16206.55	19027.26	28410.7	43831.91	53381.33	54934.33	88050.37
Growth Rates by Setting Every Last Year as Base Year							
Illiterate/Uneducated		24.00136	32.2448	47.7155	1.73106	9.2360	83.4801
Below Metric		28.78681	30.61414	45.41953	3.216797	19.62785	71.67879
Secondary		30.19157	24.17547	61.01166	2.883031	12.36546	59.40727
Higher Education Without Professional Degrees		24.67124	25.19286	61.17441	3.179027	21.74319	39.93145
Professional Degrees		17.40475	49.31577	54.27958	21.78646	2.909257	60.28296

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