ECONOMETRIC EVALUATION OF TRAINING ON EARNINGS IN PAKISTAN

Dr. Fouzia Sohail
Assistant ProfessorApplied Economics Research Centre
University of Karachi
Karachi - Pakistan
fauzia_15@hotmal.com

Lubna Naz
Lecturer
Applied Economics Research Centre,
University of Karachi
Karachi, Pakistan
syeda.lubna@hotmail.com

Dr. Sanam Wagma Khattak (Corresponding Author)
Lecturer
Department Of Economics
University of Peshawar
Peshawar - Pakistan
sanamah@uop.edu.pk

Abstract

Purpose: *The purpose of the study is to explore the effects of training on earnings of youth in Pakistan, between ages fifteen years to twenty-five years, considering the recent labour market reforms. The study specifically investigated the impact of on-job and off-job training on employees' income as an outcome variable.*

Design/ Methodology/ Approach: *The study applied an econometric technique suggested by Lalonde (1986) to avoid potential specification errors in non-experimental designs. For estimating the training impact, this study used labour force survey for the period of 2014-15. In the case of Pakistan, most of the studies based on non-experimental research design, estimated the impact of training on employees' performance using applied parametric techniques and ignored the problem of self-selection bias. This study employed non-parametric propensity score matching technique to control the issue of selection bias occurred due to the choice of workers who received training, particularly in non-experimental designs.*

Findings: *The findings of the study revealed that after controlling the self-selection, the average treatment effects of both on-job and off-job training on the employees' earnings are positive and significant.*

Originality/ Value: *Considering the current policy reforms in Pakistan, the study investigated the impact of off-job and on-job training on employees' income separately. The outcome of the study will help in evaluating the impact of huge resources, both in physical and monetary terms, diverted towards the government reforms. The study will also identify the future directions needed to equip the population with the required skills to meet the challenges of development such as CPEC.*

Keywords: Training, wages, youth JEL Classification: M53, E24, J13

1. Introduction:

Pakistan is a blessed country with the bulge of young people. Currently, the young workforce of the country makes up the largest population of its history. According to Pakistan National Human Development Report (2017), twenty-nine percent of the population are youth (15 to 29 years of age) and two-third of the population, that is, sixty-four percentage is below thirty years of age. The noticeable feature of this fact is that the future youth cohort will also comprise the largest proportion. This dynamic segment of the population could be an asset and opportunity if appropriately engaged but might twirl the country into a disaster if disregarded. Hence, it is imperative to endow this vibrant populace with skillful activities, education, training, and employment.

In this contemporary era of globalization, demand for workforce acquainted with advanced technical and technological skills has increased manifold. The recent development of China Pakistan Economic Corridor (CPEC) has enhanced the scope of the skillful workforce in every sector. However, according to the National Education Policy (2017) of Pakistan not more than twenty percent of youth completed secondary education. The proportion of youth attained technical and vocational training is even scantier. Realizing the dearth of trained youth, NAVTTC[1] had instituted 130 vocational centers across the country to train youth with needful skills under the program recognized as "Funni Mahaarat Program". According to the Economic Survey of Pakistan 2014-15, National Training Bureau also initiated various vocational training programs with affiliated bodies. It is also recognized that the system of vocational and skill development programs in Pakistan is mostly dependent on the informal sector. According to an estimate, the

[1] NAVTTC (National Vocational & Technical Training Commission) is an apex body at national level to regulate, facilitate and provide policy direction in Vocational & Technical Training.

informal ustad-shagird[2] system trains twice more people than formal training providers, institutions and NGOs. However, the official website of NAVTTC reports a total of 3634 public and private TVET institutes across Pakistan. Total TVET enrolment in registered institutes is 0.2 million across Pakistan. Hence, considering the significance of the issue for the case of Pakistan, this paper attempted to quantify the impact of training attained by the most dynamic populace of our country, ages between 15 to 29 years of age, on income. As in the current scenario, policy makers must take up these concerns on a priority basis.

Considering the current policy reforms, the foremost objective of this study is hence, to explore the effects of training on employees' earnings. As the NAVTTC targeted population are mostly not on the job, therefore the impact of training on income need to be assessed separately for off-job and on-job training imparted. The study thus investigated the impact of on-job and off-job training on employees' income (as an outcome variable) separately. For the impact evaluation, a study has applied an econometric technique suggested by Lalonde (1986). This is to avoid potential specification errors in non-experimental designs. This study first estimates the average treatment effect of overall training on individuals earning in general and then it examines the impact of on-job and off-job training in particular. In the case of Pakistan, most of the studies based on non-experimental research design estimated the impact of training on employees' performance by applying applied parametric techniques and ignored the problem of self-selection bias. This study employed non-parametric propensity score matching technique to control the issue of selection bias occurred due to the choice of personnel who received training, particularly in non-experimental designs. The findings of the study revealed that after controlling the self-selection, the study found positive and significant average treatment effects of both on-job and off-job training on the employees' earnings. For estimation purposes, this study used a labour force survey for the year 2014-15. The assessment will help in evaluating the impact of huge resources, both in physical and monetary terms, diverted towards the programs running under NAVTTC. The study will also identify the future directions needed to equip the population with the required skills to meet the challenges of development such as CPEC.

The remaining of the study is organized as follows. The next section reviews some valuable international and national literature on the issue, which is followed by the econometric model and technique employed in the study. Results are explained in section 4, which consists of two subsections. In section 4.1, the descriptive analysis of some significant variables and relationships employed in the study are explained, whereas, sub-section 4.2 reveals the empirical findings. A final section concludes the study.

2. Review of Literature:

[2] Meaning teacher-student

The difference in the wages among labours is induced mainly by the variation in human resource investment and skill enhancement (Becker, 1964 and Mincer, 1974). However, continuous up-gradation of knowledge through vocational training is the key to building skilled human capital. There is a vast literature that measures the impact of training incidence on wages. However, the impact of training types or categories of training is considered by only a few studies. For instance, Lynch (1992), Pischke (2001) distinguished between on-job and off-job training. Formal training and informal training is categorized by Pfeiffer & Reize (2001), whereas, general and specific training is differentiated by Loewenstein and Spletzer (1997). The literature thus emphasized the significance of training types, labour characteristics and job characteristics in identifying the impact of vocational training on wages via employment opportunities.

Lynch (1992) and Blundell et al. (1999) both agreed that the impact of training on wages does not necessarily relate positively but depends on the kind of training received. It is argued that specific firm related training is ineffective for other jobs thus does not enhance the labour's productivity in other jobs. Such training is believed not to be followed by a wage increase. In contrast, general training (usually off-job training) may increase the wage of labour as it increase labour productivity in other jobs as well. According to Heckman (1999), on-job training is the foremost element of human capital investment. Firms believe high returns and profitability by investing in human capital through on-job training.

On the whole, the empirical evidence does not trail in support of the unique conclusion. For instance, Mincer (1991) found the positive impact of training on wages but a negative impact on productivity. Fitzenberger and Prey (1997) compared the on-job and off-job training on income. The study found a significant and negative impact of off-job training on employment opportunities and thus wages, whereas on-job training showed a positive impact. In contrast, Loewenstein and Spletzer (1997) did not detect any significant income variability among the workers obtained general or specific training. Similarly, Lynch (1992) determined the impact of on-job and off-job training for U.S. employees. She found the insignificant impact of off-job training. Although, the results found for on-job training was positive, however, turned negative while employing the Heckman correction. Pischke (2001) revealed that training obtained in leisure time has a positive impact while negative if obtained during work hours. Black and Lynch (1996) found the positive impact of off-job training on productivity while negative for on-job training. Not only the kind of training is determined to have an impact on earning but labour characteristics (for instance qualification, age, experience) are also significant in determining this correlation.

The above review of the international literature reveals mixed results depending on the type of training received on labour's earning. Unlike international literature, scarce economic literature exists for the case of Pakistan that attempted to determine the development of technical education and training in Pakistan and its impact on income. For instance, Javeid and Hyder (2009) determine the impact of training on wages by employing cross-sectional data for the year 2005-06. The study

found an insignificant role of training, hence suggested to upgrade the training types according to the need for time. To the best of our knowledge, most of the other existing literature on Pakistan is based on evaluating various vocational training programs. For instance, Inamullah et. al. (2009), Khilji et. al. (2012), Agrawal (2013) and Ansari & Xueping (2013). However, the current study contributes to the literature not only by estimating the overall impact of training on earning but distinguishes the wage effect of on job and off job training attained specifically the youth segment of the study, by taking into account level of qualification and experience, region, marital status, gender and type of job. The next section is designed to reveal the econometric model and technique employed in the study.

3. Econometric Model and Technique:

The proposed model is based on the standard human capital earnings function of the labour market outcomes specifically participating in job training (Becker, 1964 and Mincer, 1974). To estimate the effect of job training in general, on-job and off-job training in particular, this study uses employees' earnings as an outcome variable. The treatment variable is the binary variable, 1 shows if the employee received job training and zero otherwise.
Proposed Model is as follows:

$$logEarning_i = \beta_0 + \beta_1 Age_i + \beta_2 Age\_sq_i + \beta_3 Edu_i + \beta_4 Public\_Private_i + \beta_5 Region_i + \beta_6 Treat_i + \beta_7 Emp_i + \beta_8 M\_Status_i + \beta_9 Gender_i + + \beta_{10} Sector_i + \mu i$$

Where *LogEarning* is the logarithm of employees' annual wage which is an outcome variable. *Age* represents the age of individuals. The square term is added to check the nonlinearity in the Age variable. *Edu* denotes complete years of schooling. *Public_Private* is the binary/dummy variable, where, 1 denotes for public or zero otherwise. *Treat* is the binary/dummy variable, denotes 1 for the individuals received training or zero otherwise. *Emp* is the employment status of the individuals which is categorical, where, 1 denotes employed, 2 denotes unemployed and 3 denotes not in labour force. *The region* is the region of the employment, dummy variable 1 denotes urban and 0 otherwise. *M_status* is the marital status of the individuals which is binary, 1 denotes married and 0 otherwise. Gender is another dummy variable with value 1 denotes male and 0 otherwise. The sector is a categorical variable having 3 categories; 1 denotes agriculture, 2 denotes manufacturing while 3 denotes the services sector in which individuals are involved in.

The study expects that individual earning is get affected by his/her personal characteristics and job characteristics. For example; age is expected to have a positive effect on earning because age

brings experience and higher the experience the higher will be the wages i.e $\frac{\partial logEarning}{\partial Age} > 0$. However, for the square term study expects that $\frac{\partial logEarning}{\partial Age\_sq} < 0$. For education study also expects that $\frac{\partial logEarning}{\partial Edu} > 0$ as higher education results in higher ability leading to an increase in earning potential. Further, individuals working in public sectors expected to have more stable job conditions but as far as the earnings are concern the effect may be negative or positive. As far as the numbers of earning members in the family are concerned, we hypothesis that as the numbers of earning members in the family increases, the economic well being of the household increases which may reduce or increase the earning potential of the individual members depending upon the contribution he/she has. Thus, the derivative of $\frac{\partial logEarnings}{\partial No.of\ Earners}$ could be positive or negative. For marital status being married and gender being male study hypothesis that the two would have a positive impact as both are considered responsible for the economic well being of the household hence $\frac{\partial logEarning}{\partial Gender} > 0$ and $\frac{\partial logEarning}{\partial M\_Status} > 0$. For sectoral distribution, the study assumes that individuals belonging to the manufacturing sector would be earning higher than the individuals involved in services and agriculture sectors while individuals involved in the services sector would be earning more than the agriculture sector. Finally, employment status and treat variables are included in the model to capture the role of training in succeeding employment and higher earnings. Individual with training and stable employment hypothesized to have greater earning hence $\frac{\partial logEarning}{\partial Treat} > 0$ and $\frac{\partial logEarning}{\partial Emp} > 0$.

3.1.Propensity Score Matching Technique

The Propensity Score Matching Technique (PSM) is non-parametric in nature (non-functional). PSM technique controls unobserved heterogeneity with the help of missing counterfactuals, this problem is usually appeared in non-experimental designs where bias occurred due to non-random selection of treatment . Therefore, the technique based on pure randomized experimental designs eliminate such biases[3].

This technique contains two potential outcomes such as Y_1 (for treated group) and Y_0 (for untreated). Here The treatment variable T, denotes a value 1 for the individual who is treated and zero otherwise.

[3] This methodology is adopted from Naz et.al (2018).

The causal/ treatment effect is basically the difference of potential outcomes which can be expressed as follows:

Treatment Effect (TE) = treated outcome (Y_1) - untreated outcome (Y_0)

These potential outcomes (Y_1 & Y_0) and their causal effect (TE) are randomly selected from population, therefore an individual effect can not be observed in matching experiment. Thus, an average effect that is known as average treatment effect (ATE) is calculated.

Average Treatment Effect (*ATE*) = Exp (Y_1) – Exp (Y_0)

The average treatment effect in the above notion is the expected effect of treatment "T" for individual who is randomly selected. However, treatment effect on treated can be expressed as follows:.

Average treatment effect on treated (*ATT*) = Exp (Y_1| T = 1) – Exp (Y_0|T = 1)

In order to deal with selection bias problem, matchings technique adopts two asuumptions.

Assumption 1: CIA (Conditional Independence)

It assumes that conditional on covariates X, Treatment variable T and two potential outcomes (Y_0 and Y_1) are independent. The assumption can be stated as follows:

$$Y_0, Y_1 \perp T$$

On the basis of the above assumption, the outcome Exp (Y_0|T = 1) is replaced by the outcome

Exp (Y_0|T = 0).

$$Y_{(1,0)} = \left| \quad Y_1 \text{ if } T = 1 \right.$$

$$Y_0 \text{ if } T = 0$$

$$= Y_0 + (Y_1 - Y_0)\, T$$

In above equation the term $(Y_1 - Y_0)$ denotes causal effect of treated individual and the comparison of averages by treatment gives potential outcomes.

$$\underbrace{\text{Exp}\,[Y_1 \mid T = 1] - \text{Exp}\,[Y_0 \mid T = 0]}$$

Average treatment Effect (ATE)

$$= \underbrace{\text{Exp}\,[Y_1 \mid T = 1] - \text{Exp}\,[Y_0 \mid T = 1]}_{\textit{Average treatment Effect on Treated (ATT)}} + \underbrace{\text{Exp}\,[Y_0 \mid T = 1] - \text{Exp}\,[Y_0 \mid T = 0]}_{\textit{Selection Bias}}$$

⇨ ATE – ATT = self-selection bias

Thus the difference between ATE and ATT is self-selection bias. In the absence of this bias, the ATT is called true ATT.

The matching of two groups is only possible if the employees with and without training have common characteristics. This assumption is also known as common support assumption. Thus matching is used to construct a counterfactual that is randomly selected control group who are similar to the group who were not treated.

$$\text{Prob}\,(P = 1 \mid X) = F(X) = Ps(X)$$

Where Ps(X) represents propensity scores and X is a vector of individual characteristics. Moreover, common support assumes that propensity scores (Ps) must lie between 0 and 1.

$$0 < \text{Probability } (T = 1 \mid X) < 1$$

PSM constructs matched pairs of trained individual with those untrained individuals having similar characteristic.. The study employed[4] NN matching. In NN matching the treated unit i is matched with non-treated unit j as follows:

$$\left|\mathrm{Ps_i} - \mathrm{Ps_j}\right| = min_{k\in\{D=0\}}\left\{\left|\mathrm{Ps_i} - Ps_{\mathrm{j}}\right|\right\}$$

Where, $\mathrm{Ps_i}$ and $\mathrm{Ps_j}$ are propensity scores, calculated through matching of ith individual from one group and jth individual from another group respectively. Thus the estimator calculated from nearest neigbour can be written as:

$$\text{Nearest Neighbour Average treatment Effect (NNATT)} = \frac{1}{N^{Trtt}}\sum_{\mathrm{i:Vi=1}}\left[Y_i^{obs} - \sum_{j\in U(i)D} V_{ij}\, Y_{ij}^{obs}\right]$$

$$= \frac{1}{N^{Trtt}}\sum_{i:Vi=1} Y_i^{obs} - \frac{1}{N^{Trtt}}\sum_{j\in U(i)D} W_j\, Y_{ij}^{obs}$$

Where,

N^{Trtt} indicates treated group number of observations

$W_{ij} = \frac{1}{N^u}$ if j belongs to control group of individual i and zero otherwise and $V_j = \sum_i V_{ij}$

[4] This strategy of matching suggested by Baier and Bergstrand (2009) & Abadie and Imbens (2006)

$U(i)_D$ indicates D matches set for individual i

4. Findings of the Study

4.1. Assessment of Trained Youth: A descriptive Analysis:

This sub-section of the study describes the main source of data along with the descriptive analysis of the youth segment of Pakistan under the context of vocational training attained. The primary source of data is the latest microdata of labour force survey (LFS) 2014-15, conducted and issued by the Pakistan Bureau of Statistics (PBS). The data on trained and untrained employees are extracted from this latest survey published. On the whole, the survey is comprised of 21,985 observations of the trained employees and 164,530 of non-trained employees. Additionally, out of total trained employees, 5,605 are on-job trained and 16,379 are off-job trained employees. However, this study focuses on the impact of training on youth ages between 15 to 25 years specifically. Hence the sample size consists of 6,894 trained youth against the 49,606 youth employees without any sort of training.

Table 4.1 below shows the bifurcation of trained youth concerning training type and gender. It is shown that the proportion of females equipped with training is almost equal to that of the trained male workforce; however, the incidence of on-job training is about 30 percent greater for the case of the male workforce. About 81 percent of the total trained feminine workforce acquired off job training compared to 68 percent of the male workforce.

Table 4.1: Trained youth employees by training type and gender (numbers)

Training Type	Female	Male	Total
Trained Youth Employees	3575	3319	6894
On-job Trained	670	1105	1775
Off-job Trained	2905	2214	5119
Source: LFS 2014-15			

It is observed that the incidence of on-job and off-job training depends mostly on the sort of professional training that is acquired. Similarly, some professions are specifically characterized by females, for instance, lady health workers and beauticians, whereas, others like electricians, carpentry and other technical professions are mostly adopted by males. Table 4.2 is, therefore, more support in understanding the situation.

Table 4.2: Training type by profession and gender (numbers)

Training type by profession	Female	Male	Total
Barber & Beauticians	28	81	109
Carpentry / Woodworks	--	125	126
Computer Course	155	393	548
Driving Course	22	837	859
Electrician	--	125	130
Embroidery & Knitting	790	99	889
Lady Health Visitors	2331	--	137
Mason Building	--	134	2806
Others	249	1525	1290
Source: LFS 2014-15			

Above table shows that most of the female works force opted for the training of embroidery & knitting and lady health visitors. However, the male labor force acquired mostly technical training like computer courses, driving courses, embroidery[5] and mason building.

Table 4.3: Training by Employer's Type

Training Type	Private	Public
Trained Youth Employees	3,570	96
On-job Trained	1,497	22
Off-job Trained	2,073	74
Source: LFS 2014-15		

Table 4.3 above shows the bifurcation of trained employees by type of employers, that is, private employers and public employers. The table reveals a visible and wide difference between both on-job and off-job trained workforce employed with private and public employers. It is shown that

[5] It is observed that in Pakistan most of the males who are engaged in embroidery and knitting are working on large textile and knitting industries thus working on large machineries.

more than 98.5 percent of on-job trained workers are employed in the private sector and only a mere 1.5 percent of such workers are associated with the public sector. Similarly, 96.5 percent of trained workforce, attained off-job training, are associated with private employers and only scanted 3.5 percent of off-job trained labors are employed in the public sector.

Table 4.4: Mean Wage (Rupees)

Untrained	17,135
Trained	39,003
On-job trained	58,163
Off-job trained	32,359
Source: LFS 2014-15	

Table 4.4 reveals the significant difference in the mean wage of the untrained and trained labour force for the case of Pakistan. It is shown that, on average, the wage of the trained labour force is about a hundred percent greater than that of the untrained labour force. Similarly, the average wage of workers attained on-job training is far greater than the workers attained off-job training. One foremost reason behind this noticeable difference in the wage structure between the workers' attainment of on-job and off-job training is the specialized training. It is believed that specialized, up-to-date and professional on-job training not only enhance workers' productivity but bring noticeable increment in their wage structure.

4.2. Empirical Findings:

The empirical results of the study are presented in table 4.5. The estimates of probit models are provided in tables A1 through A3. The probit model provides the propensities to estimate the average treatment effect of youth training on their earnings.

To estimates the propensities the usual procedure is to run the treatment variable (training in our case) on the various covariates designated, however, the estimates of the probit model are to envisage the propensities and thus donot provide any meaningful description. The study has firstly estimated likelihood of receiving training (overall) by regressing binary variable "training" equals 1 if received training and 0 otherwise as a function of personal characteristics (such as education, age and marital

status), household-level characteristics (such as number of earners and regional variations) and labour market conditions (for example employment status and sector employed in). After estimating the probability of receiving training the study has estimated the probabilities of receiving on the job training and finally the probabilities of receiving off-job training. The findings as stated above are annexed (see Table A1 to table A3 for detailed results).

Effects of Training on Earnings:

Table 4.5: Average Treatment Effects of Training on Earnings

Matched/Unmatched	Treated	Controls	Difference	T-stat
Unmatched	11.69	11.59	0.097	5.66
Matched ATT	11.69	11.59	0.099	3.87
Average Treatment Effects of On-Job Training on Earnings				
Unmatched	11.70	11.60	0.097	3.88
Matched ATT	11.70	11.58	0.117	3.29
Average Treatment Effects of Off-Job Training on Earnings				
Unmatched	11.68	11.60	0.076	3.64
Matched ATT	11.68	11.60	0.077	2.30

Source: Authors' calculations based on LFS, 2014-15

Table 4.5 presents the average treatment effects of youth's training on their earnings for both matched and unmatched groups. Though the treatment (training) variable is bifurcated into on-job and off-job training, so the above table is providing the ATEs of training in general and both the on-job and off-job training on employees' earning. The positive and statistically significant value of average treatment effect of unmatched group (ATE) shows that on average earning of youth employees increase by $[(e^{0.097} - 1)*100 = 10.19\%]$ for 2014-15. Further, the positive and statistically significant value of the average treatment effect on treated (matched ATT) shows that

on average youth's earnings increase by [($e^{0.099}$– 1) = 10.41%]. The matched ATT estimates are slightly higher than the unmatched group.

The second panel of the table is providing the estimates of youth's on-job training on their earnings. The positive and statistically significant estimates of on-job training reveal that workers who attained training during their job have higher earnings. The positive and statistically significant value of the average treatment effect of unmatched i.e. [($e^{0.097}$– 1)*100 = 10.19%] is lower than the matched ATT which shows that workers' earnings increased by [($e^{0.117}$– 1) = 12.4%]. Moreover, the impact of off-job training is also positive and the value of ATT provides a relatively lesser increase in employed youth's earnings. In this case, the estimate of unmatched ATE of off-job training is relatively lower i.e. [($e^{0.076}$– 1) = 7.9%] than the matched ATT estimate i.e. [($e^{0.077}$– 1) = 8.0%].

The assessment of the above ATT can be reliable if matching is effective, or, the balancing of the covariates previously and afterwards of matching is found to be valued. There are numerous procedures to check the stability of variables employed in matching. For Instance, standardized bias formula suggested for matching (Rosenbaum and Rubin, 1985), t-test for equality of means in treated and non-treated sets both before as well as after matching and graphical illustration of decrease in standardized percentage bias after matching (see Annexure).

The bias before and after matching is calculated and the change among the two is emphasized in Table A4. Column 5 of the table A4 displays the decrease in absolute standardized percentage bias after matching, in nearly all the variables. Moreover, fewer than a 5 percentage point decrease in bias after matching displays that variables are well balanced and consistent. Additionally, the t-test confirms the enhanced matching quality based on the proposition that mean values of each variable in the treated and untreated sets are similar after matching if the t-test is statistically insignificant after matching (see Tables A4 for reference).

The absolute percentage point bias for treated and the control groups before and after the matching are illustrated in Table A5. It can be detected from the table A5 that the absolute mean bias has reduced from 29.4 to 4.3 after execution of the PSM. The table also reveals that the matching is efficient as the Pseudo R^2 is displaying a lesser value. Lastly, figures A1 also depicts that the variables employed in matching deliver good matching. Figure A1 elucidated Standardized percentage bias across covariates before and after matching through the histogram. It can be detected that the standardized percentage bias has decreased significantly after the matching. On comparison, the upper panel which demonstrates the percentage bias in unmatched (non-treated group) with the subsequent panel reveals a significant decrease in percentage bias after the matching.

Grounded on the procedures presented in the study, it can be determined the (Nearest Neighbor) Propensity score matching is an effective technique to construct a comparable control group and to estimate the average treatment effect of the training on earnings in case of youth in Pakistan.

5. Conclusion and Policy Implication

This study explores the effect of training on young employees' earning in Pakistan between the ages fifteen years to twenty-five years. For estimation purposes, the study uses the latest microdata labour force survey (LFS) 2014-15, conducted and issued by the Pakistan Bureau of Statistics (PBS). The sample size consists of 6,894 trained youth against the 49,606 youth employees without any sort of training.

Descriptive analysis reveals the significant difference in the mean wage of the untrained and trained labour force for the case of Pakistan. It is shown that, on average, the wage of the trained labour force is more than twofold than that of the untrained labour force. Similarly, the average wage of workers attained on-job training is far greater than the workers attained off-job training. The study further investigated the impact of on-job and off-job training on employees' income as an outcome variable and applied an econometric technique suggested by Lalonde (1986) to avoid potential specification errors in non-experimental designs. This study first estimates the average treatment effect of overall training on individuals earning in general and then examines the impact of on-job and off-job training in particular by employing a non-parametric propensity score matching technique. This technique is useful for controlling the problem of selection bias that may occur due to the selection of employees who received training particularly in non-experimental designs. The findings reveal positive and significant average treatment effects of both on-job and off-job training on the employees' earnings.

The results of the study suggest an effective implementation of NSS (National Skills Strategy) and National TVET (Technical vocational education and training) policy that stresses on enhancing training opportunities for the youth population of the country. The effective implementation of public policies in general and specifically for youth would need public-private partnerships and effective coordination and linkage with the informal sector. It becomes imperative for the country to provide relevant skills and training with easy access and employability.

Results show that most of the female labour force attained skilled training in traditional professions like embroidery, lady health workers, etc. It is recommended that new and advanced courses and training should be designed for females for pulling them towards economically sound professions. The proper database at the level of districts, revealing the skills and occupational needs, would facilitate targeted designing and offering of the training facilities. This will also improve the spatial coverage of far-flung, remote and economical deprived areas.

It is recognized that proper, effective and targeted provision of vocational training will not only resolve the employment issues of the country but will also cater to the rising unlawful and illicit activities in the country.

References

Abadie, A., &Imbens, G. W. (2006).Large sample properties of matching estimators for average treatment effects. Econometrica, 74(1), 235-267.

Agrawal, T. (2013). Vocational education and training programme (VET): An Asian perspective. Asia-Pacific Journal of Cooperative Education, 14(1), 15-26.

Ansari, B. and Xueping, W. (2013). Development of Pakistan technical and vocational education and training : as an analyses of skilling Pakistan reforms. *Journal of Technical Education and Training*, 5(2).

Baier, S. L., &Bergstrand, J. H. (2009). Estimating the effects of free trade agreements on international trade flows using matching econometrics. *Journal of international Economics*, *77*(1), 63-76.

Becker, G. S. (1964). Human capital theory. Columbia, New York, 1964.

Black, S. E. and L. M. Lynch (1996), Human Capital Investments and Productivity, American Economic Review, 86(2):263-67 ·

Blundell R, Dearden, L, Meghir C, Sianesi B (1999) Human capital investment: The returns from education and training to the individual, the firm and the economy. Fiscal Stud. 20(1):1–23.

Fitzenberger, B., Prey, H. (1997). Assessing the impact of training on employment. *ifo-Studien* 43 71–116.

Haavelmo, T. (1943) The statistical implications of a system of simultaneous equations. *Econometrica* 11, 1–12. Reprinted in D.F. Hendry & M.S. Morgan (eds.) (1995) *The Foundations of Econometric Analysis*, pp. 477–490. Cambridge University Press.

Hechman, J.J. (1999) Policies to Foster Human Capital. National Bureau of Economic Research. Working Paper 7288.

Hyder, A. and Javaid, J. (2009). Impact of Training on Earnings: Evidence from Pakistani Industries. Asian Social Science, Volume 5, No. 11

Inamullah, H.M., Naseeruddin, M., Hussain, I, & Shah, I.H., (2009). The development of technical education in Pakistan. International Business & Economics Research Journal 8(1), 87-90.

Khilji, B.A. Kakar, Z.K and Subhan, S. (2012). Impact of Vocational Training and Skill Development on Economic Growth in Pakistan. *World Applied Sciences Journal* 17, 10: 1298-1302.

LaLonde, R. J. (1986). Evaluating the econometric evaluations of training programs with experimental data. *The American economic review*, 604-620.

Loewenstein, M. and J. Spletzer (1997). Delayed formal on-the-job training. *Industrial and Labor Relations Review 51* (1), 82{99.

Lynch, L.M. (1992), "Private-Sector Training and the Earnings of Young Workers," *American Economic Review*, 82(1), pp. 299-312.

Mincer, J. (1974). *Progress in Human Capital Analysis of the distribution of earnings* (No. w0053). Cambridge, Mass., USA: National Bureau of Economic Research.

Mincer, J. (1991), Education and Unemployment, NBER Working Paper # 3838.

National Education Policy (2017). Ministry of Federal Education and Professional Training. Government of Pakistan.

Naz, L., Ali, A., & Fatima, A. (2018).International competitiveness and ex-ante treatment effects of CPEC on household welfare in Pakistan. *International Journal of Development Issues*.

Pakistan National Human Development Report: Unleashimg the potential of a young Pakistan (2017), UNDP.

Pfeiffer, F., and Reize, F., 2001. Formelle und informelle berufliche Weiterbildung und Verdienst bei Arbeitnehmern und Selbständigen. *In:* R. K. von WEIZSÄCKER, ed. *Bildung und Beschäftigung*. Berlin: Duncker & Humblot (Schriften des Vereins für Socialpolitik, Gesellschaft für Wirtschafts- und Sozialwissenschaften; N.F., 284), pp. 215–273

Pischke, J., 2001, "Continuous Training in Germany", Journal of Population Economics, 14, 523–548.

Rosenbaum, P. R., & Rubin, D. B. (1983a). Assessing sensitivity to an unobserved binary covariate in an observational study with binary outcome. Journal of the Royal Statistical Society 45 (2), 212-218.

Rosenbaum, P. R., & Rubin, D. B. (1983b). The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), 41-55.

Rosenbaum, P. R., & Rubin, D. B. (1985a). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. American Statistician 39 (1), 33-38.

Rosenbaum, P. R., & Rubin, D. B. (1985b). The bias due to incomplete matching. Biometrics 41 (1), 103-116.

Annexures

Table A1: Estimates of Probit Model (If Training=1)

Variable	Coefficient	Z-value	P>|z|
Years of Education	-0.007	-2.35	0.02*
Age	0.234	3.65	0.00*
Square of the Age	-0.005	-3.05	0.00*
Marital Status being Married	0.064	1.96	0.05**
Employment Status			
Unemployed	-0.413	-2.58	0.01*
Not in Labour Force	-0.531	-1.98	0.05**
Region	0.003	0.13	0.90
Sector			
Manufacturing	1.508	5.32	0.00*
Services	0.648	2.29	0.02**
Public Sector	-0.317	-4.94	0.00*
Gender being Male	-0.699	-19.91	0.00*
Number of earners	0.007	3.33	0.00*
Constant	-3.767	-5.31	0.00*
No. of observations	12729		
Pseudo R^2	0.1369		
Chi-Square	2092.31*		

Source: Authors' calculations based on LFS, 2014-15
Note: *, ** and *** indicates level of significance at 1%, 5% and 10% level.

Table A2: Estimates of Probit Model (If On-Job Training=1)

Variable	Coefficient	Z-value	P>|z|
Years of Education	-0.02	-4.53	0.00*
Age	0.03	0.41	0.68
Square of the Age	0.00	-0.30	0.76
Marital Status being Married	0.10	2.38	0.02**
Employment Status			
Unemployed	-0.72	-2.84	0.01*
Not in Labour Force	-0.91	-1.95	0.05**
Region	0.14	4.24	0.00*
Sector			
Manufacturing	0.80	24.22	0.00*
Public Sector	-0.29	-2.99	0.00*
Gender being Male	-0.32	-8.02	0.00*
Number of earners	0.00	-1.46	0.14
Constant	-1.61	-2.07	0.04**
No. of observations	12729		
Pseudo R^2	0.1217		
Chi-Square	1130.70*		

Source: Authors' calculations based on LFS, 2014-15
Note: *, ** and *** indicates level of significance at 1%, 5% and 10% level.

Table A3: Estimates of Probit Model (If Off-Job Training=1)

Variable	**Coefficient**	**Z-value**	**P>|z|**
Years of Education	0.005	1.62	0.11
Age	0.299	4.18	0.00*
Square of the Age	-0.006	-3.58	0.00*
Marital Status being Married	0.001	0.02	0.98
Employment Status			
Unemployed	-0.066	-0.41	0.68
Not in Labour Force	-0.135	-0.50	0.62
Region	-0.115	-4.01	0.00*
Sector			
Manufacturing	0.819	2.89	0.00*
Services	0.334	1.18	0.24
Public Sector	-0.248	-3.60	0.00*
Gender being Male	-0.516	-14.24	0.00*
Number of earners	0.012	5.13	0.00*
Constant	-4.665	-5.98	0.00*
No. of observations	12729		
Pseudo R^2	0.0650		
Chi-Square	751.29*		

Source: Authors' calculations based on LFS, 2014-15
Note: *, ** and *** indicates level of significance at 1%, 5% and 10% level.

Figure A1: Histogram of Standardized % Bias (Training overall)

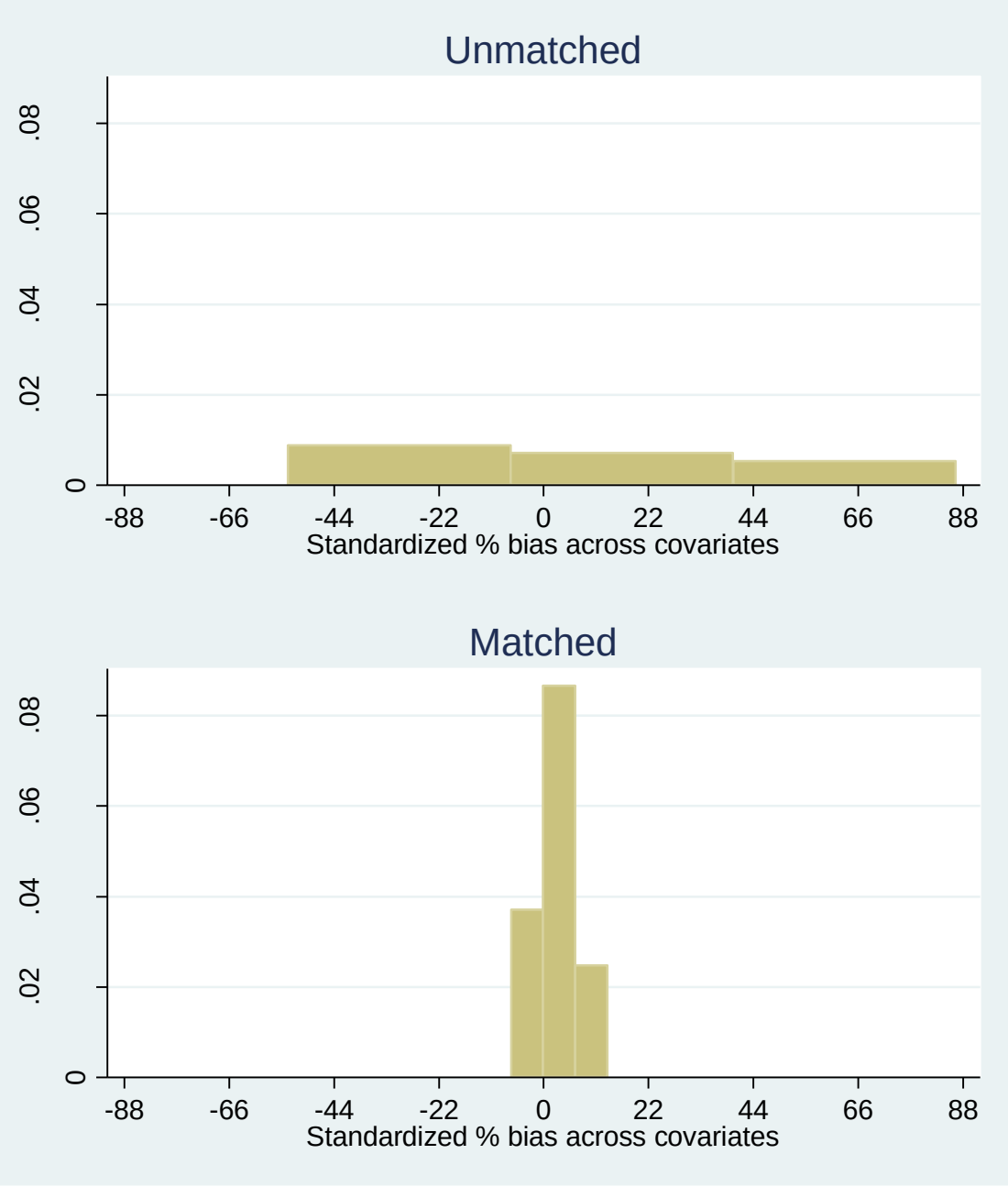

Table A4: Standardized percentage bias before/after matching

Variable		Treated	Control	%bias	% reduct |bias|	t	p>|t|	V(T)/ VC
Years of Education	U	5.94	5.9995	-1.3		-1.03	0.304	1.04
	M	6.21	5.58	13.3	-916.9	4.08	0	0.96
Age	U	20.91	19.417	49.1		36.94	0	0.83*
	M	21.32	21.168	5	89.8	1.61	0.107	0.99
Square of the Age	U	445.39	387.07	47.6		36.19	0	0.88*
	M	462.24	455.86	5.2	89.1	1.64	0.101	1
Marital Status being Married	U	0.34	0.24737	20.4		16.47	0	1.21*
	M	0.25	0.25896	-2.3	88.9	-0.7	0.485	0.97
Unemployed	U	0.02	0.06886	-24.4		-15.98	0	0.29*
	M	0.00	0.00057	0.8	96.6	1.34	0.18	3.99*
Not in Labour Force	U	0.32	0.57679	-53.7		-40.9	0	0.89*
	M	0.00	0.00057	0.1	99.8	0.58	0.564	2.00*
Region	U	0.56	0.68945	-26.6		-16.43	0	1.15*
	M	0.32	0.35686	-6.9	74.1	-2.07	0.039	0.95
Manufacturing	U	0.47	0.10834	86.6		60.99	0	2.58*
	M	0.50	0.48776	2.5	97.2	0.61	0.544	1
Services	U	0.33	0.3895	-12.2		-7.32	0	0.93*
	M	0.50	0.51167	-2.3	81.6	-0.64	0.522	1
Public Sector	U	0.03	0.06531	-18.8		-8.87	0	0.42*
	M	0.05	0.04326	4.9	73.8	1.42	0.157	1.22*
Gender being Male	U	0.48	0.50972	-5.7		-4.4	0	1
	M	0.85	0.83665	2	63.8	0.83	0.406	0.95
Number of earners	U	12.76	13.182	-6.5		-5.29	0	1.22*
	M	12.45	12.018	6.6	-1.2	2.28	0.023	1.19*

Note: * if variance ratio outside [0.95; 1.05] for U and [0.91; 1.10] for M

Table A5: Average percentage bias

Sample	Pseudo R2	LR chi2	p>chi2	Mean Absolute Bias
Unmatched	0.137	2092.31	0	29.4
Matched	0.006	29.59	0.003	4.3

Note: * if B>25%, R outside [0.5; 2]