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IMPACT OF VOCATIONAL EDUCATION AND TRAINING ON EMPLOYMENT: AN EMPIRICAL STUDY IN THE NORTHERN PROVINCE OF SRI LANKA

Sooriyakumar KRISHNAPILLAI, Ph.D., Auburn University, USA

Abstract

This paper studies the impact of vocational education and training (VET) on the probability of getting job. 4562 individuals who were randomly selected for annual labor force survey were included in this study. Nearest- neighbor matching method has been chosen for this study. The result of this study shows that VET increases the probability of getting job by 17 percent. The logit model for participation in VET indicates that the probability of participating in VET by a female student is lower than that of a male student and also the probability to participating in VET increase with schooling and decrease with age. This study suggests that more students should be admitted to the VET programme and government authority should encourage and motivate school children, especially female students, to enroll in VET programme.

Keywords: Matching; Propensity Score; Treatment Effect Model; Vocational Education and Training,

1. Introduction

Sri Lanka has produced a population with higher than 96% literacy rate in 2016. Literacy alone is not sufficient for economic growth in the knowledge era. It becomes vital to supply the labour force with skills which is needed for rapid economic growth and development. Sri Lanka has been unable to supply labour force with high quality education and skills. Sri Lanka received lower rank in providing quality of education in science and math and access to internet in schools. Sri Lanka primarily focused more on basic education in secondary level of education and less focus on higher levels of education. The mismatch between the quality of the education and the labour market requirements has led to significant unemployment of higher education institute graduates in Sri Lanka. A large number of jobs are vacant as there are no workers with the skills for the labour market requirements. Enrolment at university has dropped due to higher opportunity cost in pursuing higher education. Sri Lanka's formal education system has failed in providing market oriented skills. Technical Education and Vocational Training (TEVT) institutions in Sri Lanka became an effective alternative for students leaving from high School. TEVT institutions have helped to produce labour force with market oriented skills. Currently public, private, and NGO sector in Sri Lanka are involved in providing TEVT. Vocational training programmes became an important agenda of many governments and international donor agencies (King and Palmer, 2010). The persistence of labour market imbalances emphasized the training on market oriented skills to reduce mismatch between the quality of the education and the labour market requirements (ILO, 2012). Investing in public vocational education and training (VET) center is very important in developing countries. Due to the advancement in information and communication technology and the globalization, VET became a very important aspect of the educational development (UNESCO, 2001). VET act as a center between formal education and the labour market. VET has helped tremendously for rapid economic growth and development in South-East Asia and industrialized world. Economic benefits of VET are extensive. VET has positive impact on wages, employment, mobility, employment opportunity, productivity, innovation, and organization culture. Low rate of unemployment can have favorable consequences for national competitiveness and GDP growth. The Vocational Training Authority of Sri Lanka (VTA) established in 1995 is currently operating with 224 Rural, 22 District and 7 National Vocational Training Centers. Around 25,000 youth are trained in 18 different sectors and graduated annually from these training Centers. The objective of this study is to investigate the impact of VET on the probability of getting job.

The empirical literature on effect of vocational training on employment is extensive and reports contrasting findings. A meta-analysis by Card et al. (2018), based on 350 estimates of the employment effects of active labour market policies, confirmed significant impacts of training on women who participated in training programmes after long-term unemployment. Mo Costabella (2017) examined vocational training courses for the unemployed organized in the years 2007-2009 and found positive employment effects on women. Kumar et al. (2019) investigated the factors that affect the participation in formal vocational training and the effect of vocational training on wage in India and found that individuals with formal vocational training had higher wage in the primary and secondary sector than the individuals without formal education and enrollment of female in formal vocational education is lower than male. Vandenberg and Laranjo (2020) analyzed the impact of vocational education and training on wages and likelihood of being employed in the Philippines using propensity score matching and found that graduates of vocational education and training earned higher wages and are more likely to be employed than those who graduated from secondary school or below.

Matching method has become famous to estimate treatment effects and also extensively applied to evaluate policies in labour market (Dehejia and Wahba (1998), Heckman et al (1997)). Rosholm et al (2019) employed propensity score matching to evaluate the effectiveness of a bridging intervention which consists of classroom training, educational internships and mentoring on the educational enrollment and completion for all participants. Brunello, G., and Roccol, L. (2017) applied propensity score matching to investigate the effect of vocational education on adult skills, employment and wages. Matching can be applied in any field of study. Empirical studies have been found in various fields of study. Statisticians (Rosenbaum & Rubin, 1983) and (Heckman, 1978) have developed propensity score matching (PSM) to estimate treatment effect. Econometricians have contributed much for addressing selection bias. The PSM approach has become popular among research from various disciplines, especially economics, health, education, and substance abuse. The PSM applications have been used to evaluate child welfare programmes (Fraser, 2004), but there were arguments between advocates and adversaries of non experimental approaches. Sosin (2002) is one of the few scholars used PSM method to evaluate noneconomic programmes using non experimental approaches. The term propensity score first introduced by Rosenbaum and Rubin in 1983 to estimate causal effects between variables more precisely in their article. Estimation of treatment effects were addressed from the heckman's work on sample selection and dummy endogenous variables (Heckman, 1978). This work can be considered as a generalization of the propensity score matching.

2. Methodology

The objective of this study is to measure the effect of VET programme on the probability of finding job. To know the effect of VET on the probability of finding job by a participating individual, the observed outcome of a participating individual must be compared with the outcome that would have resulted if the participating person is not participated in the training programme. Nevertheless, only the outcome of the participating person is observed. The impact of a programme across individuals will be heterogeneous. There are two measures to estimate the effect of treatment. The average treatment effect (ATE) is the effect of participation in the programme on an individual who were randomly selected from the population. The average effect of treatment on treated (ATET) is the effect of participation in the programme on an individual who participated in the programme. The effect of the training programme can be described by two processes. First, the decision to participate in the training programme takes place. Second, the process of determining job entry happens. Selection bias can occur when some of the factors influencing the participation in programme also affect the outcome. In general, unobservable characteristics determining participation can also affect outcomes. It can be seen that highly-motivated persons most probably participate in training programme and also most probably find job. The estimated treatment effect will be biased unless sample selection issue is addressed. Roy-Rubin Model is the standard framework to formalize the sample selection problem and evaluate the treatment effect (Roy (1951), Rubin (1974)). In the case of a binary treatment, the dummy value for the treatment (D_i) = 1 if individual, *i*, is treated and 0 if not treated. The potential outcomes depends on the treatment, Q*i*(*Di*), for individual *i*,. The treatment effect for an individual *i* can be defined as:

$$\tau_i = Q_i(1) - Q_i(0) \tag{1}$$

Only one outcome is observed for each individual *i*. The unobserved outcome (counterfactual outcome) is needed to estimate the individual treatment effect, τ_i. The Average treatment effect on the treated (ATET) can be defined as:

$$\tau_{ATET} = E\,[\tau||D = 1] = E\,[Q(1)||D = 1] - E\,[Q(0)||D = 1] \tag{2}$$

The counterfactual outcome (unobserved outcome) for those being treated is defined as $E\,[Q(0)||D = 1]$. As the outcomes of individuals from treatment would differ from the outcomes of individual from comparison group even in the absence of treatment, there would be self-selection bias. Therefore, ATET can be defined as:

$$E\,[Q(1)||D = 1] - E\,[Q(0)||D = 0] = \tau_{ATET} + E\,[Q(0)||D = 1] - E\,[Q(0)||D = 0] \tag{3}$$

The true parameter τ_{ATET} is only identified if `self-selection bias' is equal to 0

$$E\,[Q(0)||D = 1] - E\,[Q(0)||D = 0] = 0 \tag{4}$$

To solve `self-selection bias' problem, some identifying assumptions should be made. The average of differences between the outcomes of treated and non-treated is the mean effect of treatment. Average treatment effect (ATE) is defined as:

$$\tau_{ATE} = E[Q(1) - Q(0)] \tag{5}$$

In the method of matching, a matching individual for every individual in the treatment group is found from among the comparison group by identifying individuals sharing similar observable characteristics. The probability of finding a match reduce when the number of characteristics considered in the matching process increases. Rosenbaum and Rubin (1983) showed that matching on all covariates as a single index formulated based on the chance of participation could achieve reliable estimates of the treatment effect. This matching is called propensity score matching. To generate a propensity score for each observation, a logit regression model is developed with treatment as the dependent variable and the potential covariates as explanatory variables. After generating propensity score, it must be ensured that graph (series) of propensity scores across treatment and control groups are overlapped and the propensity score should be balanced in the treated and control groups. And also individual covariates across treatment and control groups within blocks of the propensity score should be balanced. After creating a balanced propensity score, it can be used to compare treatment and control groups. Matching and weighting strategies are most popular among the comparison strategies (Austin 2009, 2011). There are a number of possible ways of identifying this matched group. Kernel matching uses multiple comparators to match each treatment group member. Matching balances characteristics across the treatment and matched control groups. The extent of matching can be determined by examining the propensity score's distribution in the treatment and matched control groups and also by comparing standardized differences. Covariates are strongly related to the outcome if there are small differences in means of covariates (Ho et al. 2007).

The data randomly collected by Department of Census and Statistics for 2014 annual labour force survey from five districts of Northern Province of Sri Lanka were used for this study. The data of the individuals who are 15 years old and above and not going to school include 1539, 811, 800, 752 and 656 individuals from Jaffna, Vavuniya, Mannar, Kilinochchi and Mullaitivu districts respectively. Totally, 4562 individuals were included in our study. The variables considered in this analysis are age, gender, education level, vocational training, employment, Cross sectional data of these variables were used to develop the models for the probability of getting job, using treatment effect estimation..

3. Results and Discussion

The descriptive statistics of variables considered in this analysis are given in Table 1. Average age and average education level of individuals selected for this study are 42 years old and around 9th grade respectively. 48% of these sample individuals are employed. Among 4562 individuals, 272 individuals (6%) got vocational education and training. A logit regression was developed with participation in the VET (treatment) as dependent variable and gender, age, and education level as explanatory variables to create a propensity score for each observation.

Table 1: Description and descriptive statistics of the variables

Variable	description	Obs	Mean	Std. Dev.	Min	Max
Gender	If male, dummy value is 1 Female is 0	4,562	.4715	.499	0	1
Age	Number of years	4,562	42.85	16.60	15	65
Education	Number of years of schooling	4,562	8.680	3.232	0	17
Employment	if employed, dummy value is 1 Unemployed is 0	4,562	.4813	.499	0	1
VET	If participated in VET, Dummy value is 1 If not is 0	4,562	.0596	.236	0	1

The logit model for the participation in the VET was given in Table 2. Graph of propensity scores (Figure 1) indicates that propensity scores across treatment and comparison groups are overlapped. The balance test divides the treatment group into 8 blocks on the basis of the propensity score and showed that mean propensity score is significantly indifferent for treated and comparison group in each block and also the individual covariate of the treatment and comparison groups are significantly indifferent from each other within these blocks. This implies that the distribution of propensity score within each block is similar across groups and that the propensity score is correctly specified.

Table 2: Model for Participation in Vocational Education and Training

Variable	coefficient	z	p value
Gender	-0.39	-2.82	0.005
Age	-0.027	-5.18	0.000
Education	0.529	16.6	0.000
Constant	-7.183	-17.09	0.000

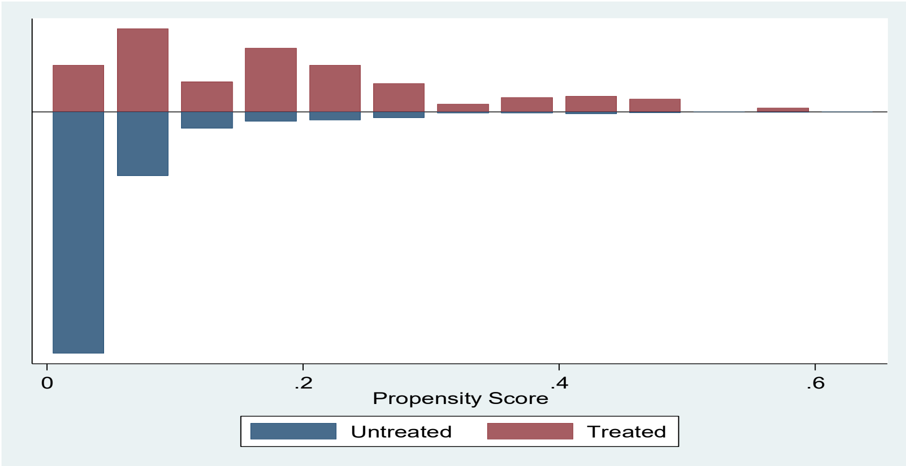

Figure 1: Distribution of Propensity Score across Treatment and Comparison Groups

After creating a balanced propensity score, logit models were employed to estimate the average treatment (VET) effect on the individuals participated in the VET (ATET) and on the individuals randomly selected from the population (ATE) using different matching and weighting estimators. How well the treatment and comparison groups balanced were tested by comparing standardized differences, propensity score graph of covariates, propensity score graph of treated and control group before and after matching or weighting. ATET and ATE estimated from different matching and weighting estimator and summary of balance statistics were presented in Table 3 and Table 4 respectively. After comparing the standardized differences given in Table 3, the smallest standardized difference in the matched or weighted covariates were found when estimating treatment effect on treated individuals (ATET) using the nearest matching method. The smallest standardized difference, the propensity score graph of treated and control (Figure 2) and the propensity score graph of covariates (Figure 3, 4 and 5) before and after matching or weighting indicate that treatment and comparison groups well balanced when estimating ATET using nearest-neighbor matching method. Therefore, nearest- neighbor matching method has been chosen to evaluate the effect of VET on participants (ATET) in this study. The estimate of ATET of nearest- neighbor matching method (0.13) indicates that probability of finding employment by a participant in VET increases by around 13 percent. As shown in Table 4, the smallest standardized difference in the matched or weighted covariates were found when using the nearest matching method to estimate treatment effect on randomly selected individuals (ATE).

Table 3: Average Treatment Effect on Treated and Statistics of Different Matching and Weighting

Matching/ Weighting Estimator	ATET	Variable	Number of Treated observations Matched/ Weighted	Number of Comparison observations Matched/ Weighted	Raw	Standardize difference Matched/ Weighted
Nearest Matching Neighbor	.132	gender	272	272	-.192	0
	(0.000)	age			-.701	.003
		Education			1.399	.002
Inverse Probability Matching (IPW)	.123	gender	2,241	2,321	-.192	.0013
	(0.000)	age			-.701	.0019
		Education			1.399	-.077
Regression adjusted With IPW	.131	gender	2,241	2,321	-.192	.0013
	(0.000)	age			-.701	.0019
		Education			1.399	-.077
Propensity Score Matching	.127	gender	272	272	-.192	0
	(0.005)	age			-.701	.089
		Education			1.399	.026

Table 4: Average Treatment Effect and Balance Statistics of Different Matching and Weighting .

Matching/ Weighting Estimator	ATE	Variable	Number of Treated observations Matched/ Weighted	Number of Comparison observations Matched/ Weighted	Raw	Standardize difference Matched/ Weighted
Nearest Matching Neighbor	.172 (0.034)	gender	4,562	4,562	-.192	0
		age			-.701	-.25
		Education			1.399	.31
Inverse Probability Weighting (IPW)	.213 (0.000)	gender	1,940	2,622	-.192	.0296
		age			-.701	-.496
		Education			1.399	.407
Regression adjusted With IPW	.240 (0.000)	gender	1,940	2,622	-.192	.0296
		age			-.701	-.496
		Education			1.399	.407
Propensity Score Matching	.268 (0.156)	gender	4,562	4,562	-.192	.209
		age			-.701	-.427
		Education			1.399	.0356
Augmented Inverse Probability Weighting	.203 (0.000)	gender	1,940	2,622	-.192	.0296
		age			-.701	-.496
		Education			1.399	.407

P-value in Parentheses

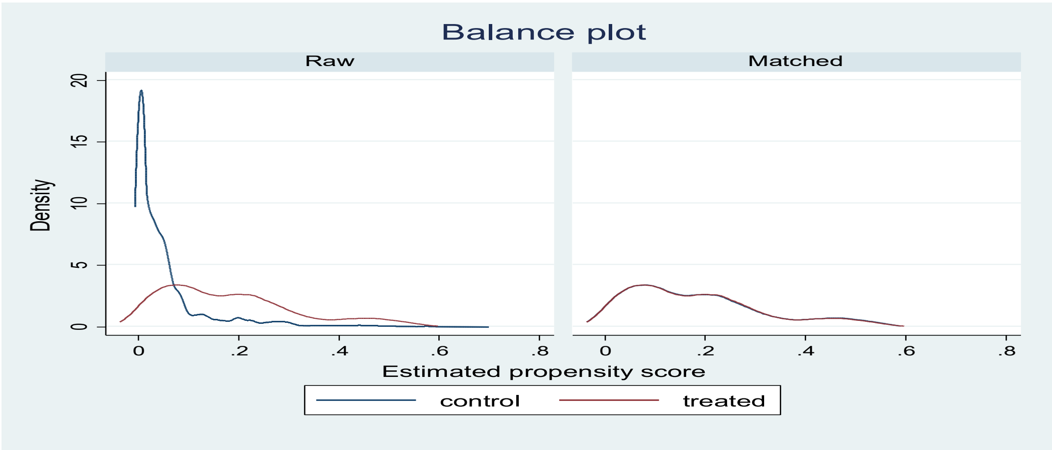

Figure 2: Balanced Plot of Treated and Control Groups (ATET)

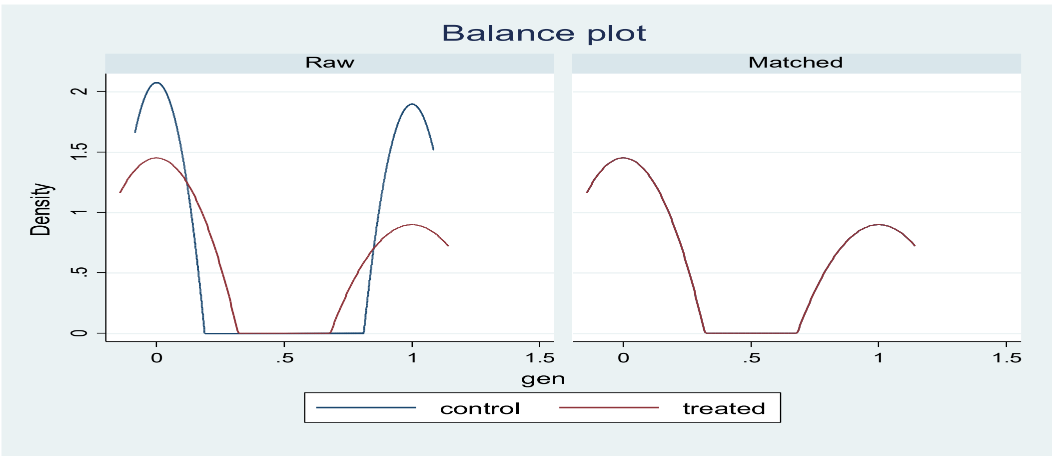

Figure 3: Balance Plot of Gender (ATET)

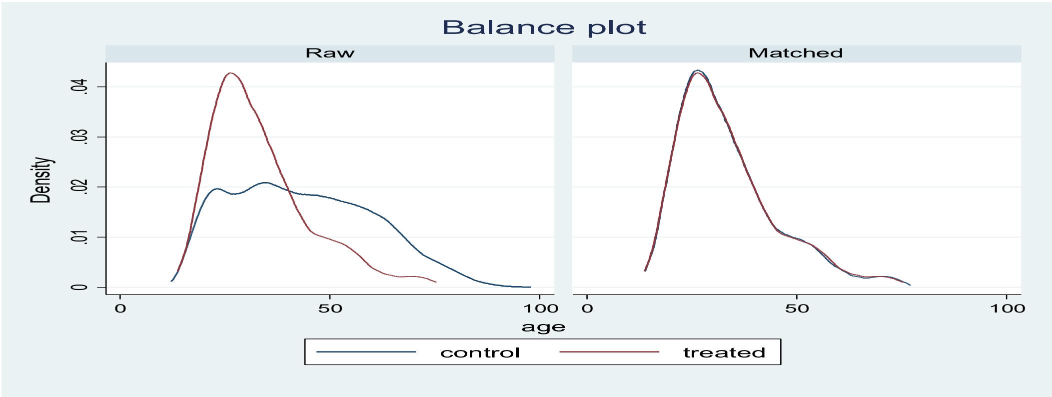

Figure 4: Balance Plot of Age (ATET)

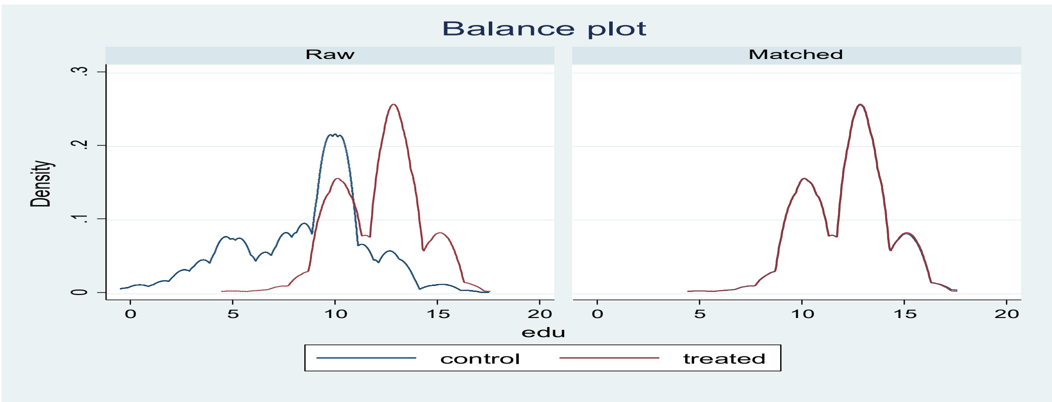

Figure 5: Balance Plot of Education (ATET)

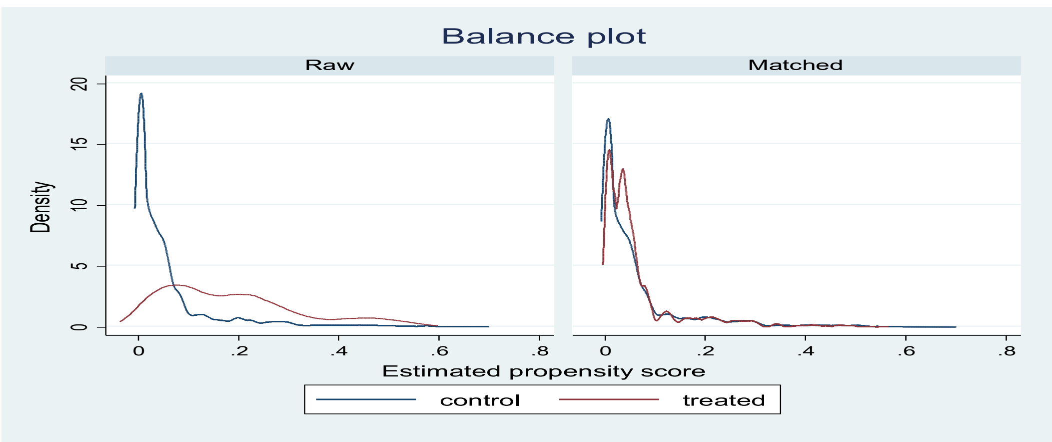

Figure 6: Balance Plot of Treated of Control Group (ATE)

The propensity score graph of treated and control (Figure 6), the propensity score graph of covariates (Figure 7, 8 and 9) before and after matching or weighting and the smallest standardized difference indicate that treatment and comparison groups well balanced when using nearest-neighbor matching method in this study. Therefore, nearest- neighbor matching method has been chosen to evaluate the effect of VET on participants (ATE) in this study. The estimate of ATE of nearest- neighbor matching method (0.172) indicates that probability of finding employment by a randomly selected individual increases by around 17 percent after completing VET. As shown in Table 2, the logit model for participation in VET shows that the probability of participating in vocational education and training by a female is lower than that of a male student. Every additional year of schooling of a student increases the probability to participate in VET. Coefficient of age implies that the probability to participate in VET decreases with age.

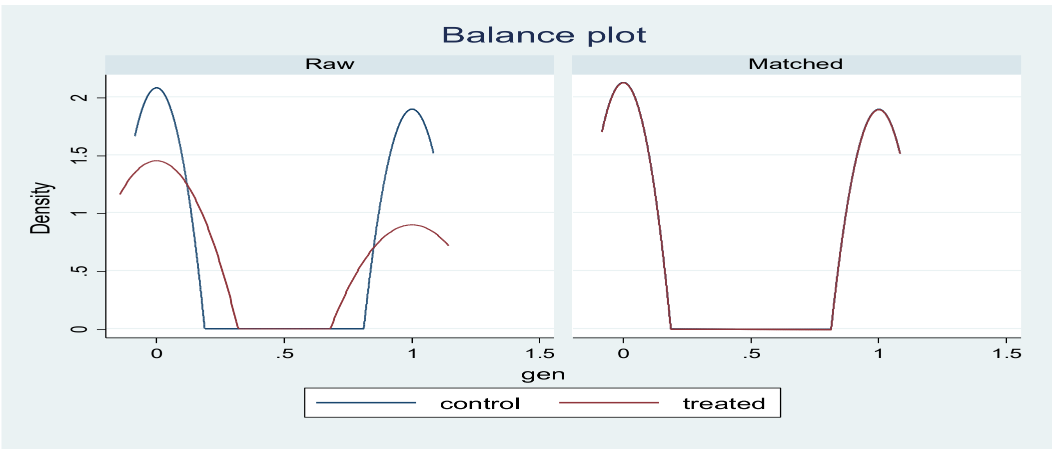

Figure 7: Balance Plot of Gender (ATE)

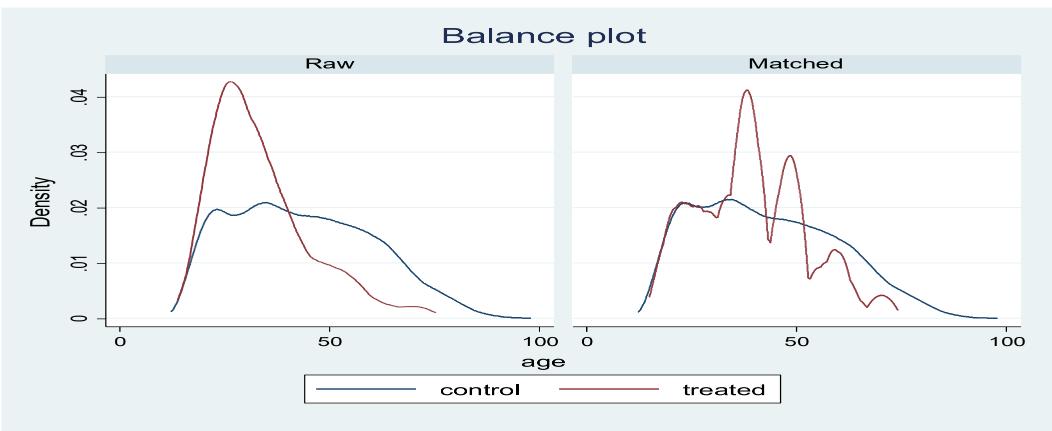

Figure 8: Balance Plot of Age (ATE)

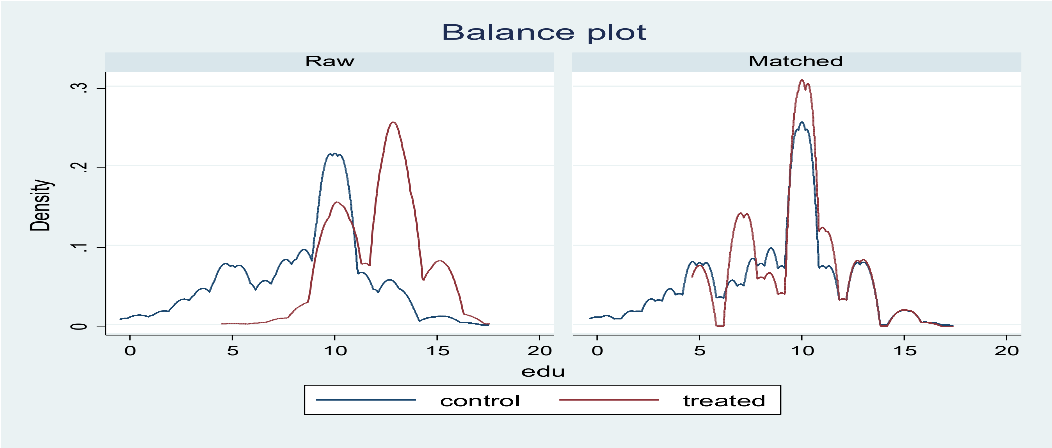

Figure 9: Balance Plot of Education (ATE)

4. Conclusion

This study concludes that probability of finding employment by a participant in VET increases by around 13 percent and probability of finding employment by a randomly selected individual increases by around 17 percent after completing VET. The logit model for participation in VET indicates that the probability of participating in VET by a female is lower than that of a male student and also the probability to participating in VET increase with schooling and decrease with age. This study suggests that more students should be admitted to the VET programme and awareness programme about VET should be conducted to motivate the school students; especially to female students, to enroll in VET

References

Austin PC, (2009). Balance Diagnostics for Comparing the Distribution of Baseline Covariates between Treatment Groups in Propensity-Score Matched Samples. *Statistics in Medicine*, 28:3083–107.

Austin PC, (2011). A Tutorial and Case Study in Propensity Score Analysis: An Application to Estimating the Effect of In-Hospital Smoking Cessation Counseling on Mortality. *Multivariate Behavioral Researc*h, 46:119–51.

Brunello, G., and Roccol, L. (2017). The effects of vocational education on adult skills, employment and wages: What can we learn from PIAAC?, SERIEs https://doi.org/10.1007/s13209-017-0163-z

Card, D., Kluve, J., & Weber, A. (2018). What works? A meta analysis of recent active labour market program evaluations. *Journal of the European Economic Association*, 16(3), 894–931.

Dehejia, R. H., and Wahba, S. (1998). Matching Methods for Estimating Causal Effects in Non-Experimental Studies, Working Paper 6829, National Bureau of Economic Research.

Fraser MW, (2004). Intervention research in social work: Recent advances and continuing challenges. R*esearch on Social Work Practice*, 14(3):210–222.

Heckman, J. (1978). Dummy endogenous variables in a simultaneous equations system. *Econometrica*, 46, 931-961.

Heckman JJ, Ichimura H. Todd PE, (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program. R*eview of Economic Studies*. 64:605–54.

ILO,(2012). *Upgrading informal apprenticeship, a resource guide for Africa*, ILO.

King, K., and Palmer, R. (2010). *Planning for technical and vocational skills development.* UNESCO: International Institute for Educational Planning, Paris.

Kumar,R, , Mandava.V., and Gopanapalli. S.V, (2019). Vocational training in India: determinants of participation and effect on wages, *Empirical Research in Vocational Education and Training*, 11: 3, https://doi.org/10.1186/s40461-019-0078-y

Mo Costabella, L. (2017). Do high school graduates benefit from intensive vocational training?. *International Journal of Manpower*, 38(5), 746-764

Rosenbaum, P., and D. Rubin, (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70, 41 - 50.

Rosholm M, Mikkelsen MB, Svarer M, (2019). Bridging the gap from welfare to education:

Propensity score matching evaluation of a bridging intervention. *PLoS ONE* 14(5): e0216200. https://doi.org/10.1371/journal.pone.0216200

Roy, A.(1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers*, 3, 135 - 145.

Rubin, D. (1974) Estimating Causal Effects to Treatments in Randomised and Nonrandomised Studies. *Journal of Educational Psychology*, 66, 688 - 701.

Sosin, M. R. (2002). Outcomes and sample selection: The case of a homelessness and substance abuse intervention. *British Journal of Mathematical and Statistical Psychology*, 55, 63-91.

Vandenberg.P, and Laranjo. J, (2020). *The Impact of Vocational Training on Labor Market Outcomes in the Philippines*, ADB Economics Working Paper Series No 621, DOI: http://dx.doi.org/10.22617/WPS200274-2

UNESCO (2001). *Revised Recommendation Concerning Technical and Vocational Education and Training.* (Paris, UNESCO)