The Impact of Technical and Vocational Education and Training on Youth Employment Outcomes in the Philippines[1]

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Abstract

Young people have been disproportionately affected by the COVID-19 crisis through multiple channels: job losses; disruptions in education and training; and delays in labor market transitions — with long-term ramifications on their employment and earning prospects. These underscore the critical role of the technical-vocational education and training (TVET) system in the post-pandemic recovery and in navigating the future of work, especially among the youth. This study estimates the impact of TVET on youth employment outcomes, such as labor force participation, employment, and underemployment. Using labor force survey and applying inverse-probability weighted regression adjustment estimators, this study finds that TVET program completion improves labor force participation of young individuals not in school or training. However, TVET program completion has no significant positive impact on the employment and underemployment of young graduates. The study concludes with a discussion on how to expand the scope of the study in terms of examining other key dimensions of employment quality, the sample, and resolving identified data issues and gaps.

I. Overview

The economic crisis triggered by the onset of the COVID-19 pandemic has compounded pre-existing labor market challenges faced by the youth. Young people have been disproportionately affected by the crisis through multiple channels: job and working hour losses; disruptions in education and training; and delays in labor market transitions. The massive job and working hour losses of the youth can be attributed to their overrepresentation in low-productivity, low-paid, and less secure jobs and in hard-hit sectors of the economy, prior to the crisis. Prolonged closures of schools and training institutions have stalled their human capital development, through limited and restricted engagement in upskilling and reskilling initiatives, such as technical and vocational education and training (TVET). Finally, these disruptions to education, training, and work-based learning, coupled with the unprecedented contraction in demand, hampered the labor market transitions of the young jobseekers and new labor market entrants, as they compete against more experienced and older workers in a tight and evolving labor market. Ultimately, young people being not in employment, education, or training (NEET) have adverse ramifications on their long-term employment and earning prospects of the youth, with risks of further economic and social exclusion.

These underscore the critical role of the technical-vocational education and training (TVET) system in the post-pandemic recovery and in navigating the future of work, especially among the youth. One of the primary goals of TVET, as per the TESDA NTESDP 2018–2022 (TESDA 2018) is to equip its trainees with useful and relevant skills to make them workforce-ready and globally competitive. Thus, this study estimates the impact of completing a TVET program on youth employment outcomes, such as labor force participation, employment, and underemployment.

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[1] This study draws heavily from my working paper, which became Chapter 8 – *Employment Outcomes for Technical and Vocational Education and Training Graduates* of an ADB TVET study, entitled "Technical and Vocational Education and Training in the Philippines in the Age of Industry 4.0".

This study starts by providing an overview of the literature examining the relationship between engagement in TVET and employment outcomes. This is followed by a brief discussion of the data and methodology employed in the study. Then, estimates on the impact of TVET on employment outcomes are presented. It concludes with a discussion on how to expand the scope of the study in terms of examining other key dimensions of employment quality, the sample, and resolving identified data issues and gaps.

II. Literature review

There are myriad studies assessing the employment effects of active labor market programs such as TVET, on the youth in different country development contexts. The empirical evidence across countries and regions vary. Using meta-analysis methods, Kluve et al. (2016) identify and review evidence of 113 counterfactual impact evaluations, which utilize different interventions, methods across countries. They find that only one-third of these youth employment programs have shown a significant positive impact on labor market outcomes, either in terms of employment rates or earnings. Using a similar methodology, but on 97 studies between 1995 and 2007, Card, Kluve, and Weber (2010) assess the effects of ALMPs on employment and determine that programs that target the youth are less effective in bringing positive effects. This affirms an earlier review by Kluve and Schmidt (2002) on studies on European ALMPs between 1983 and 1999. Most of these studies are in the context of high-income countries. Interestingly, however, Kluve et al. (2016) and Betcherman et al. (2007) determine that youth interventions in low- to middle-income countries are more effective in improving employment outcomes than in high-income countries.

Estimated employment impacts, are mixed, with a range of contrasting findings across available studies. For instance, in the context of low- to middle-income countries, McKenzie (2017) provides recent evidence on the effects of ALMPs and reveals that many of these are much less effective than policymakers perceive, with evaluations estimating no significant impact on employment and earnings. By contrast, Tripney and Hombrados (2013) focus their assessment from studies in Latin American countries and show that TVET interventions have small, positive, and significant mean effects on overall paid and formal employment, and monthly earnings. Attanasio, Kugler, and Meghir (2011) study the impact of a unique randomized training program in Colombia and identify that it significantly raises the earnings and employment outcomes for women. Hicks (2011) describes how the ongoing Technical and Vocational Vouchers Program in Kenya had positive supply-side impacts among institutions and short-run impacts, not only on labor market outcomes, but also on expectations and behaviors of participants. Bidani et al. (2009) use different methodologies to assess the employment effects of public retraining programs in two cities in the People's Republic of China, Wuhan and Shenyang, and find strong evidence to suggest that the programs improved employment of workers in Wuhan but not in Shenyang.

Although TESDA collects and publishes regular statistics (e.g., graduate tracer surveys) and studies (e.g., employment satisfaction survey reports) on TVET graduates, the literature estimating the employment impact of TVET in the Philippines has been scant. These statistics have not yet been analyzed rigorously to establish correlation and causality of TVET on employment outcomes such as earnings, employment, employability and mismatch. Nevertheless, the numbers suggest that, despite important employment gains, TVET graduates experience high unemployment and underemployment rates. Using the individual graduate tracer surveys covering graduates from 2010–2017, TVET graduates' overall unemployment rates were found to decline from 60% to 70% before training to between 28% and 35% post-training. Despite these gains in employment post-training, unemployment rates remain high, and 37% to 43% of employed graduates are considered underemployed or still want additional hours of work. Using a unique dataset, the World Bank STEP Survey, Vandenberg and Laranjo (2021) employ probabilistic regression techniques to estimate the effects of TVET on employment and find that TVET graduates are more likely to be employed.

Employment outcomes are determined by both demand-side and supply-side factors, and the interaction of the two. Specifically, there needs to be demand for the output of TVET (i.e., employment opportunities

must exist), the output of TVET needs to be adequate to meet this demand in terms of quantity (no excess supply of graduates in certain fields), and quality (meeting industry standards and employer expectation, i.e., employability). Thus, employment outcomes are not equivalent to employability, which is one of the factors determining these outcomes. Using the Philippines Enterprise Survey of World Bank in 2015, Acosta et al. (2017) present evidence of inadequate workforce skills, particularly in terms of socio-emotional skills, usually known as “noncognitive skills”, “soft skills”, or “behavioral skills”. About one-third of employers cites difficulty in filling vacancies, primarily attributing to the skill shortage of applicants.

The Employer and Training Institute Surveys conducted by ADB also provide valuable insights on the quality of TVET graduates employed in the IT-BPO and Electronics industries (ADB 2020). The survey results of employers in the IT-BPO industry reveal that employers are somehow satisfied with the graduates in terms of “general” and “job-specific” skills, with about 51%– 55% of firms with a positive response (strongly agree and agree). However, industry interviews highlighting some challenges employers face in finding qualified graduates, consistent with Acosta et al. (2017), which identifies lack of skills or competency as the top reason for the unfilled vacancies in the industry. There seems to be better satisfaction on the overall skill level of graduates among employers in the electronics industry. The Employers Survey for the industry shows that 58% of employers agree that graduates possess the right level of “general” and “job-specific” skills and are ready for entry-level occupations.

The perspective of training institutions on the quality of their graduates are reflected in the results of the training institute survey. Training institutions point to the lack of recognition of certifications by employers and the lack of preparedness of their graduates as the top employment barriers. Comparing the results from the two surveys reveals the wide discrepancy in terms of the expectations of training institutions and employers on the skill level of graduates: 90% of training institutions are optimistic of their graduates’ labor market preparedness while only 52% and 58% of employers from the IT-BPO and electronics industries respectively agree. ADB (2020) further concludes that the implementation and the content of these skills training often do not match industry requirements.

III. Data and Methodology

Data

LFS data are used for information on the employment outcomes and program characteristics of young individuals who completed a TVET program and those who did not.[2] This study uses the October (3rd Quarter) round of LFS in 2018 to account for the first set of graduates of the Senior High School (SHS) program, which consists of a Technical-Vocational-Livelihood (TVL) track[3] for students.[4] Our sample of interest is young individuals aged 15 to 24 years old who are neither in school nor in training.[5] Also, this

[2] Starting April 2016, the LFS adopted the 2013 Master Sample Design, with a sample size of approximately 44,000 households. In terms of generating the labor force statistics, the population projections are based on the 2010 Census of Population and Housing (Philippine Statistics Authority 2012).
[3] The TVL track allows students to learn skills and earn requisite COCs (Certificates of Competency) and NCs (National Certifications) which might boost their career opportunities.
[4] The first set of SHS graduates are those graduating in Academic Year 2017-2018. The potential youth samples in years before the implementation of the K to 12 program are substantially different from those post-implementation. Thus, we carefully restrict our analysis to those after the program and avoid comparing across years before the reform.
[5] Note that only the 2018 LFS contains information on whether the individual is currently attending a TVET program or not and in school or not. Still, the other two rounds have information on whether he/she is currently in school or not.

paper excludes individuals for whom we do not have information about their parents' education.[6] The importance of this variable is further discussed in the next section. The summary statistics of the sample are presented in Annex B.

The main limitations of using the LFS are the lack of information on the timing, duration, and other characteristics of the TVET program completed by the individual. The lack of information on timing and duration implies that the TVET course could have been completed at any point in the individual's life, while his/her employment status is measured at the specific point in time of the survey. Restricting the sample into this young cohort partially reduces the magnitude of this timing problem. The LFS also lacks information on program characteristics, such as type, sector, modality, in the survey. Thus, we cannot use LFS to analyze the program characteristics of the graduates who benefitted the least or most from completing TVET.

Methodology

This study uses treatment effect methods for the assessment of employment outcomes of TVET.[7] We are interested in three sets of outcomes of our sample: labor force participation, employment and underemployment status. We evaluate these employment outcomes using labor force survey data.

<u>Treatment-effects estimators</u>

Since treatment status in this case is obtained from observational data, it is therefore not randomized. This suggests that our outcome and treatment variables are not necessarily independent. Thus, this study uses treatment effects estimators to utilize the covariates to ensure that treatment and outcome are independent after conditioning on those covariates.[8] This study measures the treatment effect or the average causal effect of a variable, commonly binary, such as TVET completion, on an outcome variable of interest, which is an employment outcome in our context. However, the problem with using observational data is that all the potential outcomes of the same individual cannot be observed, which gives rise to the missing-data problem and thus no estimates for individual-level effects.[9] Given the binary nature of our outcome variable, we employ the inverse-probability weighted regression adjustment (IPWRA).[10]

IPWRA is a doubly robust estimator that combines the outcome modeling strategy of Regression Adjustment (RA) and the treatment modeling strategy of inverse probability weights.[11] If the treatment models are well-specified, then the outcome will be conditionally independent of the treatment and the covariates are balanced (i.e., the distributions of covariates do not vary over treatment levels). Before inferring from the results of the treatment effect estimation, this study employs an overidentification test for covariate balance. [12] The null hypothesis of the test is that the treatment model balanced the covariates. Thus, the rejection of the null hypothesis implies that the covariates are still unbalanced and the estimates are unreliable. Further, to account for possible endogeneity, i.e., the treatment assignment is correlated with the potential outcomes, this study uses endogenous treatment effects estimators to calculate treatment

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[6] The relevant question for classifying an individual as a parent in the LFS does not distinguish between father or mother. To maximize the number of individuals in the sample, all three, including household head, are used as the bases for identifying one as a parent.
[7] The background and technical details of the empirical methodology are presented in Appendix A.
[8] For a detailed description of treatment effects estimators used and its assumptions, see Appendix A.
[9] Potential-outcome models provide a solution to these by specifying the potential outcomes that each individual would obtain under each treatment level, the treatment assignment process, and the dependence on the treatment assignment process. See Appendix A for an elaborate discussion.
[10] Other treatment effect estimators are regression adjustment estimators, inverse-probability-weighted estimators, doubly robust estimators, and matching estimators.
[11] See Appendix A for the assumptions, functions, and step-by-step process of this estimator.
[12] This follows the suggestion of Rubin (2008). This post-estimation test was derived by Imai and Ratkovic (2014).

effects.[13] Specifically, using a probit model for both the treatment assignment and potential outcomes, this study estimates the two models using the endogenous treatment-effects estimators. Finally, to verify the presence of endogeneity in our sample and, therefore, decide on the more appropriate estimator, we perform a post-estimation test, i.e., a Wald test. The null hypothesis of the test is that the correlations are jointly zero. Thus, rejection of the null hypothesis would suggest endogeneity and justify the use of the endogenous treatment effect estimator over the IPWRA and other treatment effect estimators.

IV. Main findings

Evidence that TVET causes young individuals to be part of the labor force is confirmed using the IPWRA method. Specifically, we find that for the population of TVET graduates, the average labor force participation rate would be 76.7% in the counterfactual case of no TVET (Table 1). Thus, among TVET graduates, TVET completion increases the average labor force participation rate by an average of 6.2 percentage points. These results make intuitive sense because the willingness of TVET graduates to upskill and reskill through TVET implicitly suggests that they are relatively more determined and motivated to look for work and participate in the labor market than non-graduates.

TVET program completion has no significant positive impact on employment for young TVET graduates. When none of the individuals in the sample completes a TVET program (i.e., in the counterfactual case of no TVET), the average employment rate is 83.2% (Table 1). The estimated average treatment effect is insignificant. This suggests that the average employment rate when all the individuals in the sample complete a TVET program is not significantly different from the counterfactual case of no TVET. This set of findings can be possibly explained by a myriad of factors. The lack of soft and technical skills among TVET graduates coupled with the lack of recognition of certifications by employers may be the primary employment barriers as highlighted by ADB (2020). The existence of a mismatch between the skills demanded in the labor market and the skills graduates gained from TVET is also a possibility.

When evaluating the possible employment effects of TVET, we must also extend our analysis, not only in terms of improved employment rates, but also in the quality of jobs they are employed in. One aspect of job quality is assessing whether the individual is experiencing underemployment, which in this study refers to time-related underemployment.[14] Other key dimensions are level of formality, working conditions and just compensation.

The empirical results suggest that TVET does not help solve the youth underemployment problem. This is confirmed by the regression results using IPWRA. In particular, we find that for the population of TVET graduates, the average underemployment rate would be around 15% in the counterfactual case of no TVET (Table 1). TVET completion increases the average underemployment rate by 5.9 percentage points among TVET graduates. This can be attributed to the large proportion of enrollment in programs leading to occupations that are non-routine manual in nature and low-paying in the Philippine labor market. One of the reasons for the influx of demand for this type of programs is the employment opportunity and corresponding relative high pay in such occupations overseas. The impacts of other program-specific characteristics on underemployment are discussed in the succeeding subsection.

Table 1. Average Treatment Effect on the Treated (ATET) of TVET on Employment Outcomes using IPWRA Estimators, 2018

	Labor force	Employed	Underemployed
	0.062***	-0.001	0.059**

[13] See Appendix A for the detailed description of endogenous treatment estimators.
[14] Underemployed are defined as employed persons who express the desire to have additional hours of work in their present job or an additional job, or a new job with longer working hours)

Average treatment on the treated (ATET)	(0.021)	(0.023)	(0.027)
Potential Outcomes	0.767***	0.832***	0.146***
	(0.011)	(0.009)	(0.010)

*** p<0.01, ** p<0.05, * p<0.1
Source: Author's estimates.

Results of the test for covariate balance suggest that the employment outcomes are conditionally independent of TVET completion and justify the use of IPWRA estimator (Table 2). In particular, the estimates from the overidentification test imply that we do not find sufficient evidence to reject the null hypothesis that the covariates are balanced. This implies that the distributions of the covariates do not vary over treatment levels and the treatment effect estimates can be used for inference.

Table 2. Overidentification Test for Covariate Balance

Dependent variable	
Labor force participation	26.71
	(0.22)
Employment	22.54
	(0.43)
Underemployment	19.83
	(0.59)

The p-values of the chi-squared test statistic are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Source: Author's estimates.

The Wald test statistics following the endogenous treatment effects estimation point to an absence of endogeneity and further validates the use of IPWRA estimators (Table 3). Except for the outcome variable of underemployment, which is only significant at the 10% level of significance, the results suggest that we do not find enough evidence to reject the null hypothesis of no endogeneity. This implies that the unobservable factors that determine employment outcomes are not correlated with the decision to complete a TVET program. This, ultimately, the IPWRA estimator, which gives correct standard errors, is preferred and appropriate for the all the employment outcome models.

Table 3. Wald Test for Endogeneity of the Unobservable Characteristics

Dependent variable	
Labor force participation	1.17
	(0.5571)
Employment	1.53
	(0.4663)
Underemployment	5.87
	(0.0532*)

The p-values of the chi-squared test statistic are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Source: Author's estimates.

V. Conclusions and ways forward

The role of TVET in upskilling and reskilling the labor force has never been more crucial, due to the challenge of rapidly changing landscape of work brought about by Industry 4.0 and the widespread job displacement across sectors caused by COVID-19. Certain industries (i.e., tourism, transportation, etc.) and demographic groups (i.e., youth and women) have been disproportionately affected by these two phenomena. In this context, TVET has the potential to effectively facilitate the smooth transitions of workers across jobs and industries and aid in the economic recovery during and after the pandemic.

This study found strong evidence of a causal impact of TVET on the labor force participation of young individuals not in school nor in training. In particular, using the IPWRA estimator, we found that TVET completion increases the average labor force participation rate of graduates by an average of 6.2 percentage points compared to the counterfactual case (i.e., had they not completed any TVET program).

Although the positive effects of TVET on labor force participation should be acknowledged, it is of particular interest to policymakers and stakeholders of the training system to know whether TVET leads to employment among the youth. The treatment effect estimates from the IPWRA estimators show that TVET program completion has no significant positive impact on employment for young TVET graduates.

Looking at aspects of employment quality, we find that TVET does not help solve the problem of youth underemployment. The results suggest that even when TVET leads to employment, this is apparently more likely to be in occupations where workers still desire additional working hours, look for an additional job or even a new job with longer hours. These findings suggest further monitoring and evaluation in terms of the nature of jobs TVET graduates take post-training. It is not enough for graduates to be employed in any type of job but ideally in occupations that they trained to be competent for. The issue of training-job mismatch must be carefully studied and addressed effectively.

This study can be further extended by analyzing other key dimensions of employment quality such as level of formality, working conditions, and just compensation. In addition, the scope of the study may be expanded to include not just young individuals not in school nor in training but the entire labor force. This will only be possible, however, if data collection techniques are continually improved and expanded to include TVET drop-outs. Not all LFS rounds contain information on the basic characteristics (i.e., public or private, type and level) of the TVET course taken and completed of the individual. Such data would have provided important insights on specific program characteristics and its employment correlates. Finally, inclusion of the year the individual completed his or her TVET program, if possible, would resolve the timing issue that arises when using the LFS as the primary source of data for this type of analysis.

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Appendix A. Empirical methodology

A. Treatment effects estimators

The problem with using observational data is that all the potential outcomes of the same individual cannot be observed, which gives rise to the missing data problem and thus no estimates for individual-level effects. Potential-outcome models[15] provide a solution by specifying the potential outcomes that each individual would obtain under each treatment level, the treatment assignment process, and the dependence of the

[15] This is also known as the Rubin causal model and the counterfactual model. For detailed discussions, refer to Rubin (1974) and Wooldridge (2010, chap. 21).

potential outcomes on the treatment assignment process. There are three assumptions that need to be satisfied before using treatment effect estimators. These are the independent and identically distributed (i.i.d.) sampling, conditional-independence, and the overlap assumption. The i.i.d. assumption assures that the outcome and treatment status of each i are unrelated with that of other individuals in the population. The sampling technique used in collecting the data to be used in our study satisfies this condition. The overlap assumption states that each individual has a positive probability of receiving treatment. Anyone from our sample can participate and complete a TVET program. Conditional-independence is a strong assumption which does not need to be met if we are interested in estimating the average treatment effect on the treated (ATET). That is, estimating the impact of TVET on employment outcomes among graduates. We must only satisfy the conditional mean independence (CMI) assumption, which states that, after accounting for the covariates $\boldsymbol{X}_i$, the treatment does not affect the conditional mean of each potential outcome.

1. Inverse-probability weighted regression adjustment (IPWRA)

IPWRA possesses a property where only one of the two models need to be specified correctly to obtain correct estimates of the treatment effect.[16] It is an RA estimator that adopts the estimated inverse-probability weights. This puts weights on the regression adjustment equations using the propensity scores to achieve balance between treatment and comparison groups as indicated by balance in the covariates.

We use the IPWRA estimators to predict TVET program completion and employment outcomes. The estimation process follows the following steps to estimate the treatment effects:[17]

1. Estimate the parameters of the treatment model as in Equation 1 using a logit regression.

$$\boldsymbol{T}(\boldsymbol{S}_i) = \beta_0 + \boldsymbol{\beta}\boldsymbol{X}_i + \varepsilon_i \quad (1)$$

   Where $\boldsymbol{T}$ is the binary treatment status of being a TVET graduate or not, $\boldsymbol{X}_i$ refers to educational attainment, parents' education, potential work experience and location.

2. We then derive the predicted value of the probability or propensity score, $\widehat{\boldsymbol{T}}(\boldsymbol{S}_i)$, from the model and use it as inverse-probability weights.

3. Fit the weighted regression models of the employment outcomes (Equation 2) for each treatment level using the estimated inverse-probability weights from Step 2

4. Fit the weighted regression models of the employment outcomes (Equation 2) for each treatment level using the estimated inverse-probability weights from Step 2.

$$\boldsymbol{Y}_i = \begin{cases} (\alpha_0 + \boldsymbol{\alpha}\boldsymbol{W}_i + \mu_i)\left[pw = \dfrac{\widehat{\boldsymbol{T}}(\boldsymbol{S}_i)}{1 - \widehat{\boldsymbol{T}}(\boldsymbol{S}_i)}\right] & if\ T_i = 1 \\ \alpha_0 + \boldsymbol{\alpha}\boldsymbol{W}_i + \mu_i & if\ T_i = 0 \end{cases} \quad (2)$$

   Where $\boldsymbol{Y}_i$ is a vector of binary employment outcomes (e.g., employed or unemployed, underemployed or not,[18] and out of the labor force or not), $\boldsymbol{W}_i$ pertains to educational attainment,[19] parents' education, potential work experience and its square, marital status, and urbanity.[20]

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[16] See Cattaneo (2010) for a detailed discussion.
[17] Refer to StataCorp (2015).
[18] We define underemployed as those employed persons who express the desire to have additional hours of work in their present job or an additional job, or a new job with longer working hours.
[19] We included Grade 11 and 12 in the group of high school graduates.
[20] For a detailed theoretical discussion of doubly robust estimators, refer to section 21.3.4 of Wooldridge (2010).

5. Compute the means of the treatment-specific predicted outcomes. The differences of these averages for the subset of TVET graduates, in comparison to non-graduates, are the ATETs (Equation 3).

$$\boldsymbol{ATET} = \frac{1}{N_G}\left[\sum_{i\in G} Y_i^G - \sum_{j\in N} \omega(i,j)Y_j^N\right] \quad (3)$$

where N_G is the number of TVET graduates i, $\omega(i,j)$ is the weight of the aggregated outcomes of non-graduates j.

Before inferring from the results of the treatment effects estimation, we follow the recommendation of Rubin (2008) to ensure that the treatment model balanced the covariates. This implies that the distributions of the covariates do not vary over treatment levels. To verify this, we implement an overidentification post-estimation test for balanced covariates, *tebalance overid,* developed by Imai and Ratkovic (2014). The null hypothesis of the test is that the covariates are balanced. Rejection of the hypothesis suggests the need to revise the model. Otherwise, we can proceed with inferring from the estimates of the treatment effects estimators.

2. Endogenous treatment effects estimators

Suppose we suspect that the treatment assignment is correlated with the potential outcomes. In other words, enrolling and completing a TVET program is not independent of the potential employment status of the individual. This violates the CMI assumption and implies an endogeneity problem. If that is the case, we apply the endogenous treatment-effects estimators to calculate the treatment effects. It is an extension of RA estimators but relaxing the CMI assumption. Moreover, it fits our purposes given that it allows for binary outcomes and treatment variables.

To address the potential endogeneity of the treatment assignment, the residuals from the treatment model (Equation 5) will be included in the potential outcome model (Equation 6), known as the control-function approach.[21]

$$\mathrm{P}\ (\mathbf{T} = 1 \mid \mathrm{Z} = \mathrm{z}) = \boldsymbol{\Phi}\ (\beta_0 + \boldsymbol{\beta}\mathbf{Z} + \mu) \qquad (5)$$

such that $\mathrm{E}\ (\ \mu \mid \mathrm{T}\ )\ \neq 0$, suggesting endogeneity and **T** is the binary treatment status of being a TVET graduate or not, **Z** is a vector of controls such as educational attainment, parents' education, potential work experience, and location.

$$\mathrm{P}(\mathbf{Y} = 1|\mathbf{W}, \boldsymbol{\mu}, \mathbf{T}\ ) = \boldsymbol{\Phi}(\alpha_0 + \boldsymbol{\alpha}\mathbf{W} + \gamma\mu + \varepsilon)\ \forall\ \mathrm{T} \in (0, 1) \quad (6)$$

where μ is the residual from Equation 5, **T** is the binary treatment status of being a TVET graduate or not, **Y** is a vector of binary employment outcomes (e.g., employed or unemployed, underemployed or not, and out of the labor force or not), and **W** pertains to the set of controls which include educational attainment, parents' education, potential work experience and its square, marital status, and urbanity.

It must be noted that the bases of the control function estimator are Equation 5, endogeneity, $\mathrm{E}\ (\mu \mid \mathrm{T}) \neq 0$, and independence of the ε with **Z**. Using probit models for both the treatment assignment and potential outcomes, we estimate Equations 5 and 6 using the endogenous treatment-effects estimators and calculate

[21] See Wooldridge (2010) for an elaborate and clear discussion, which includes the conditions and assumptions for the validity of the estimator.

the treatment effects (Equation 7). The main difference between Equation 4 and Equation 7 is the specification of the outcome models where they are derived from, which are Equation 3 and Equation 6, respectively. The former allows for endogeneity, while the latter uses inverse probability weights.

$$\mathbf{ATET} = \hat{Y}_i^{G} - \hat{Y}_i^{NG} \qquad (7)$$

Where N_G is the number of TVET graduates N_{NG} the number of nongraduates.

Finally, to verify endogeneity, we perform a post-estimation test, a Wald test, which determines whether the estimated correlations between our two models are significantly different from zero, which is possible given the control-function approach of the estimator.

Appendix B. Summary statistics

Table A1. Summary Statistics of the Sample, 2018

Variable	2018
TVET status	
Non-graduate	94.0%
Graduate	6.0%
Educational attainment	
High school undergraduate and below	36.0%
High school graduate	30.2%
Some college and post-secondary education	18.3%
College and beyond	15.5%
Sex	
Female	41.2%
Male	58.8%
Age	20.9
Marital status	
Single	83.4%
Married	15.6%
Others	1.1%
Number of observations	11,821

TVET = technical and vocational education and training.
Note: The estimates are weighted using survey weights.
Source: Author's estimates.

Table A2. Employment Status by Selected Demographic Groups, 2018

Variable	Unemployed	Employed	Not part of the labor force
TVET status			
Non-graduate	11.5%	58.9%	29.6%

Graduate	14.1%	68.5%	17.4%
Educational attainment			
High school undergraduate and below	7.9%	61.0%	31.1%
High school graduate	12.5%	57.4%	30.1%
Some college and post-secondary education	14.2%	56.7%	29.1%
College and beyond	16.0%	63.3%	20.7%
Sex			
Female	11.8%	47.2%	41.0%
Male	11.6%	68.0%	20.4%
Marital status			
Single	13.2%	59.1%	27.8%
Married	4.4%	61.3%	34.3%
Others	2.4%	64.0%	33.6%

TVET = technical and vocational education and training.
Note: The estimates are weighted using survey weights.
Source: Author's estimates.

Table A3. Underemployment Status by Selected Demographic Groups, 2018

Variable	Not underemployed	Underemployed
TVET status		
Non-graduate	85.4%	14.6%
Graduate	80.1%	19.9%
Educational attainment		
High school undergraduate and below	81.3%	18.7%
High school graduate	83.5%	16.5%
Some college and post-secondary education	88.4%	11.6%
College and beyond	92.4%	7.6%
Sex		
Female	90.3%	9.7%
Male	82.5%	17.5%
Marital status		
Single	86.1%	13.9%
Married	79.5%	20.5%
Others	84.3%	15.7%

TVET = technical and vocational education and training.
Note: The estimates are weighted using survey weights.
Source: Author's estimates.