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Abstract

Youth unemployment is a major political issue in many countries, including Sri Lanka, where unemployment among young is pervasive. Vocational education and training (VET) has been identified as an effective solution to match between the labor demand and supply. Using a fuzzy regression discontinuity design (FRDD), we examine the effectiveness of VET on youth employment in Sri Lanka. We find that VET improves short-term employment outcomes, but has limited impacts on permanent contracts, career advancement, and wage progression. The economic crisis further exacerbated employment insecurity, leading to a higher job turnover and shift toward self-employment. The heterogeneity analysis across VET courses reveals that those impacts are not uniform, and graduates in selected courses tend to gain more. Our findings underscore the importance of stronger industry linkages, enhanced job security measures, and tailored VET curricula to ensure sustained labor market integration and long-term career progression for vocational graduates in Sri Lanka.

Key Words: Youth Unemployment, Vocational Education and Training, Labor Market Dynamics, Sri Lanka

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1. Introduction

Youth unemployment is one of the key global challenges faced by both developed and developing countries (Chakravarthy et al., 2019; Dagume and Gyekey, 2016). The world youth unemployment rate ranged from 16 percent to 13 percent between 2015 and 2024, while in South Asia, it was recorded between 20 percent and 14 percent over the same period (ILO, 2025). The lack of skills and knowledge, as well as skills mismatch with labor market demands, are considered the root causes of youth unemployment in many developing countries (Das, 2020; Msigwa and Kipesha, 2013). Long-term youth unemployment could intensify the negative economic, social, and political consequences, such as higher poverty, income inequality, and undesirable trends in economic development (Sam, 2016). Moreover, it could intensify social crises, including crime, civil conflicts, depression, drug addiction, social exclusion mentality, and suicides (Chakravarthy et al., 2019; Nattrass, 2002).

Investing in Vocational education and training (VET) is considered one of the best tools to develop productive human capital and a sustainable solution for youth unemployment (Das, 2021). VET can enhance job-specific skills for immediate global labor market needs and secure the pathway to enlarge employment opportunities (Blumenfeld and Malik, 2017; Lavrijsen and Nicaise, 2017; Olfindo, 2018; Rongguang, 2001). Institutions such as the World Bank and UNESCO often describe the VET programs as the silver bullet against youth unemployment and a key to supporting sustainable development (Eichhorst et al., 2015: Tikly, 2013).

However, existing studies show mixed results on the effect of VET on labor market outcomes. Some evidence in the developed context, especially the countries with a strong VET system, such as Switzerland (Oswald-Egg and Renold, 2021) and the Netherlands (Muja et al., 2019), shows a positive effect on labor market outcomes. Similar positive effects appear in the youth guarantee scheme in Latvia (Bratti et al., 2018), a popular active labor market policy in Romania (Popescu and Roman, 2018), and the public-sponsored job training in Japan (Hara, 2022). However, other studies have demonstrated the nuanced results of the effect of VET on employment and wages in middle-income countries, South Asia, and Latin American Countries (Newhouse and Suryadarma, 2011; Tripney and Hombrades, 2013; Chakravarthy et al., 2019; Das, 2021). Such mixed evidence may suggest that the impact of VET is context-specific, contingent on the place and period under study.

In this study, we examine the causal impact of VET on various youth labor market outcomes in Sri Lanka. As a developing nation in South Asia, Sri Lanka has experienced a serious youth unemployment issue. The youth unemployment rate increased from 19.2 percent to 21.6 percent between 2013 and 2016 (Department of Census and Statistics, 2018), and further to 25.9 percent in 2020 (Department of Census and Statistics, 2020). Moreover, the 2022 economic crisis, driven by high debt, dwindling foreign reserves, and surging inflation, resulted in severe shortages of basic necessities and widespread social unrest. This downturn had a considerable impact on youth unemployment (ILO, 2022). Despite the policy emphasis of VET on labor market outcomes, there is limited research providing statistical evidence of the impact of VET in Sri Lanka. We address this research gap by analysing the original data collected from around 5,000 VET applicants in 2015-2017, which track the first employment, and employment status in 2022 (peak of economic crisis) and in 2023 (post-crisis) to capture their occupational dynamics.

More specifically, using entrance exam scores as a running variable, we exploit the fuzzy regression discontinuity design (FRDD) to estimate the causal impact of VET. While propensity score matching has been widely used to estimate the impact of VET, it may not fully address the issue of selection bias inherent in non-randomized studies (Guo et al., 2020). The FRDD offers a more robust method by leveraging cutoffs in program eligibility, providing more credible causal inference. We consider vocational applicants whose score is above the threshold of the entrance exam as a treatment group and those below the threshold as a control group. Then, we conducted the follow-up surveys to collect information from both graduates and non-graduates of VET on education and employment dynamics for one year, and five to six years after graduation, in order to examine the short-term and longer-term effects. The study also examines the heterogeneous effect by types of VET programs on labor market outcomes.

We find that participation in VET in Sri Lanka significantly increases the likelihood of employment immediately after graduation. However, the overall analysis reveals that VET graduates are predominantly placed in low-income and temporary job roles, with limited access to long-term permanent contracts or career progression over time. While short-term employment gains are evident, long-term outcomes, including income mobility and job-skills alignment remain weak, especially in the post-crisis period following the 2022 economic downturn. The heterogeneity analysis further highlights substantial variation across course categories. VET graduates from fields such as Finance, Banking and Management (FBM) and Electrical and Electronic Technology (EET) experienced better labor market transitions, while several other courses like Agriculture (APL), Building and Construction (BC) and Information, Communications and Multimedia (ICM) showed even adverse effects, such as delayed employment and heightened vulnerability during economic shocks. These findings underscore the need for both system-level reforms and course-specific interventions to enhance the effectiveness of VET as a pathway to sustainable employment.

The paper expects to contribute to the literature on VET in developing countries, mainly in the following three ways. First, using FRDD, the paper provides solid empirical evidence of the impact of vocational programs targeted at junior high school leavers on labor market outcomes in all the provinces of Sri Lanka, which remains rare in the Sri Lankan context. The second contribution of this study is the investigation of heterogeneous effects across different vocational course categories. By analyzing variations in employment success, job stability, and wage progression across six vocational fields, this study provides empirical insights into the relative effectiveness of each course category. These findings will help determine the most productive vocational programs, enabling policymakers to strengthen high-performing courses while revising or improving curricula in less effective fields.

The third contribution is a thorough analysis of how VET affects various labor market outcomes over time. These include employment status, job transitions (particularly in the first employment, 2022, and 2023), monthly income, job type, relevance of skills, and long-term career growth. A key focus is the impact of Sri Lanka's 2022 economic crisis on VET graduates, particularly in sectors like construction, where early studies suggest significant effects on job security and wages (ILO, 2022). By analysing these dynamics, this study provides critical insights into how economic shocks affect vocational graduates, guiding curriculum revisions and policy interventions to enhance the resilience and effectiveness of VET programs for sustainable human capital development.

The remainder of the paper is organized as follows. In Section 2, we discuss the background information on Sri Lankan vocational education and training systems and institutions. Section 3 describes Data and Sample Selection; Section 4 explains the Empirical Strategy; Section 5 discusses the Results and Discussion . Finally, Section 6 explains the Conclusion.

2. Background of Vocational Education and Training

In Sri Lanka, the formal VET sector comprises about 635 public sector training institutions and 718 private and non-governmental organization (NGO) training institutions. A large number of non-formal VET providers also provide training in information technology (IT) on a fee-for-service basis, and there is a widespread network of non-fee-levying institutions that are funded by various national and international charities. VET, in association with the Skills Development Project (SDP) and with funding from the Asian Development Bank (ADB), developed the National Vocational Qualifications (NVQ) framework and National Competency Standards (NCS) in consultation with industry (UNESCO, 2018). The curricula, trainer guides, trainee guides, and assessment resources are all based on these standards. Assessments are competency-based, and the system is benchmarked against qualification systems in developed countries.

There are seven National Vocational Qualification levels in Sri Lanka, from 1 to 7 NVQ levels. 1 to 4 are equivalent to certificate levels, which provide entry-level competencies and craftsmanship and are targeted for Ordinary Level (Junior high school) completed students. NVQ levels 5 and 6 are equivalent to diploma levels that provide technical level to management level competencies and are targeted for Advanced level (High school) completed students. NVQ 7 is equivalent to a bachelor's degree. The Technical Colleges provide vocational courses from NVQ 2 to NVQ 6 under the eighteen categories (Table 1). Thirteen categories have been provided for NVQ 4, 5, and NVQ 6 courses.

Table 1

NVQ Level of the courses.

NVQ Level	Course Category
1, 2 & 3	Hotel & Tourism Leather and Footwear Office Management Textile and Garments Wood Related
4, 5 & 6	Agriculture plantation & livestock Automobile repair and maintenance Building & construction Electrical, electronics & telecommunication Finance banking & management Food technology

	Gem & Jewellery
	Information communication & multimedia technology
	Languages
	Mechatronic technology
	Metal and light engineering
	Refrigeration & air conditioning
	Trainer training

Source: Department of Technical Education and Training, 2019

This study focuses on NVQ level 4 courses since the students gain both medium-level management competencies and practical technical skills from the technical college and internship. Moreover, the course completion rate is high for NVQ 4 courses, which makes it more accurate to measure the impact in terms of statistical power.

3. Data and Sample Selection

The characteristics (ex: education level, residential area, age, marital status, parental income, and applicant baseline income) of VET applicants for this study were collected from the application forms in 2015, 2016, and 2017, whereas data on the selection procedures of the Vocational Colleges, including entrance exam scores and the results, were obtained from the Technical Colleges. The labor market outcomes data after graduation were collected from the original interviews of the applicants in 2015, 2016, and 2017 by using several strategies as follows: (1) collected VET graduated applicants' current information through class teachers at the Technical Colleges; and (2) contacted both treatment and control group applicants through phone call interviews, and in-person interviews.

This study focuses specifically on graduates who completed National Vocational Qualification (NVQ) Level 4, which constitutes the highest standard level of technical and craft-based competencies within Sri Lanka's national vocational training framework. One of the core objectives of NVQ Level 4, as outlined in national skills development strategies, is to foster entrepreneurship and self-employment pathways, particularly for youth in technical trades. NVQ Level 4 maintains significantly higher enrolment and completion rates compared to advanced NVQ levels such as Level 5. By focusing on Level 4 graduates, this study captures the largest and most policy-relevant segment of vocational education completers, particularly those expected to transition directly into the labor market without pursuing higher academic or technical qualifications. The selection of this group is also aligned with national priorities to strengthen mid-level skills development and expand opportunities for youth-led entrepreneurship.

Table 2 below shows the total number of applicants in each category in 2015, 2016, and 2017. Among the applicants for each NVQ 4 program, the colleges selected the students for enrolment based on entrance examination scores due to the limited capacity for each course. The applicants who get the marks above the cut-off are eligible to enroll in vocational programs, while those below the cut-off marks are not. Those cut-off marks differ from one course to another.

The Treatment Assigned includes both "Registered" and "Selected but not Registered applicants" (no-shows): The "Registered" applicants passed the entrance exam, registered, and actually followed the course; and the "Selected but not registered" applicants were qualified, but did not register for the course. The Control Assigned includes both "Not Selected" and "Not Selected but Registered" (crossovers) applicants. The "Not Selected" applicants are disqualified from the course because they failed the entrance exam. The "Not Selected but Registered" applicants are disqualified from the entrance exam but registered to follow the course. These applicants are very small, and they got the opportunity to register for the vacant spaces at the technical colleges presumably because some qualified applicants did not register. Because of such non-compliance, this study applies FRDD, as will be discussed in detail below. Table 2 presents the total number of applicants and status by each course category from 2015 to 2017.

Table 2

Number of Applicants to the NVQ 4 Course Categories.

			Course Categories					
Group	Status	Year	Agriculture Plantation and Livestock	Automobile Repair and Maintenance	Building and Construction	Electrical, Electronics and Telecommunication	Finance Banking and Management	Information Communication and Multimedia
Treatment Assigned	Registered	2015	98	388	1615	442	398	783
		2016	296	635	2967	651	444	1199
		2017	434	1223	3200	750	662	1210
	Selected but Not Registered	2015	133	327	1891	591	622	894
		2016	141	421	1144	273	509	651
		2017	95	368	1069	416	279	732

Control Assigned	Not Selected	2015	46	205	731	184	192	455
		2016	182	384	1211	279	403	2294
		2017	92	392	1034	262	297	1935
	Not Selected but Registered	2015	-	22	127	38	46	20
		2016	21	66	181	58	51	45
		2017	18	81	273	76	59	36

In this study, the population is identified as all the applicants of the following six course categories in 2015, 2016, and 2017; a) Agriculture Plantation and Livestock (APL); b) Automobile Repair and Maintenance (ARM); c) Building and Construction (BC); d) Electric, Electronic and Telecommunication (EET); e) Finance, Banking and Management (FBM); f) Information Communication, and Multimedia Technology (ICM). We restrict the analysis to these NVQ 4 courses because they have sufficient sample observations. We reached out to all possible applicants from the phone call interviews to get the data and collected data from all agreed-upon respondents. To determine the sampling strategy, this study first gathers the entrance exam scores of applicants along with the cut-off marks for each course. It then selects sample observations within a bandwidth near the cut-off mark and conducts interviews. The bandwidth is expanded as needed based on reachability.

Table 3

The total number of complete observations of this study.

Group	Status	Year	Course Categories					
			Agriculture Plantation and Livestock	Automobile Repair and Maintenance	Building and Construction	Electrical, Electronics and Telecommunication	Finance Banking and Management	Information Communication and Multimedia
Treatment Assigned	Registered	2015	-	31	150	36	54	93
		2016	62	134	451	107	115	251
		2017	54	141	426	159	93	189
	Selected but Not Registered	2015	-	3	5	2	2	13
		2016	3	4	36	9	6	11
		2017	2	7	11	6	7	4
Control Assigned	Not Selected	2015	-	28	109	28	27	66
		2016	22	97	349	87	91	284
		2017	17	109	358	121	57	207
	Not Selected but Registered	2015	-	2	3	2	1	6
		2016	2	3	29	7	5	12
		2017	2	3	4	4	3	4

Table 3 presents the total number of observations for which we successfully collected relevant data. We initially contacted 23386 applicants via phone interviews and obtained data from 4988 individuals (2882 from the treatment assigned and 2106 from the control group). After data cleaning, 4734 remained for analysis.

We acknowledge that some individuals who were assigned to the program, but did not enroll (no-shows), could not be reached due to practical constraints. To assess whether this non-response could bias our findings, we conducted balance tests on pre-determined covariates such as age, gender, and education level between the respondents and non-respondents to the survey. As shown in Appendix Table 5, no significant differences were found in pre-treatment characteristics between respondents and non-respondents, suggesting that attrition is unlikely to bias the results. This supports the internal validity of our FRDD estimates among compliers.

Table 4

Descriptive Statistics.

	Variable	Mean	Median	Std. dev.	Min	Max	Observations
Pre-determined characteristics	Gender (Male=1)	0.549	1	0.498	0	1	4734
	Age	28.437	28	2.323	24	41	4734
	Marital status (Married=1)	0.481	0	0.500	0	1	4734
	Number of children	0.204	0	0.449	0	4	4734
	Parental income[2]	2.126	2	1.061	1	6	4734
	Education level (O/L=1)	0.745	1	0.436	0	1	4734
	Pre household members	4.265	4	1.132	2	8	4734
	Pre-professional course (Yes=1)	0.331	0	0.471	0	1	4734
	Pre working experience (Yes=1)	0.207	0	0.405	0	1	4734

Table 4 presents the descriptive statistics for the demographic characteristics of the sample. The sample is approximately gender-balanced, with 54.9% being male**.** The average age is 28 years**,** with a range spanning from 24 to 41 years**.** A majority of the sample remains unmarried**,** and the average household size is four**.** The parental income most commonly falls within the 20,001–40,000 LKR[3] range**,** indicating a middle-income background. In terms of

[2] Parental income is measured in Sri Lankan Rupees (LKR) using six response categories. Respondents could select only one option from the following ranges: (1) 0–20,000, (2) 20,001–40,000, (3) 40,001–60,000, (4) 60,001–80,000, (5) 80,001–100,000, and (6) above 100,001. **A median value of 2 for parental income indicates that the most typical response was category 2, meaning the average parental income falls within the 20,001–40,000 LKR range.**

[3] 20000-40000 LKR equal to 66.89 -133.79 USD

education, 74.5% of the respondents hold an Ordinary Level (O/L) qualification, which is equivalent to a junior high school education qualification. Regarding prior professional exposure, a significant portion of vocational applicants had not pursued any professional courses before enrolling in VET (only 33.1 percent had prior professional education), and only 20.7 percent had prior work experience.

4. Empirical Strategy

In this study, the identification strategy exploits the fact that applicants are allowed to enter a VET if they have an entrance exam score above the cut-off, which leads us to employ a regression discontinuity design to estimate the causal impact of entering to VET. This addresses the selection into VET based on the assumption that exam scores cannot be manipulated. However, as explained earlier, there is imperfect compliance: some applicants with exam scores above the cut-off did not enroll in VET (no showers), while some applicants below the cut-off enrolled in it (crossovers). Thus, we employ an FRDD, which enables us to obtain a less biased estimate compared to simple ordinary least squares (OLS) with some non-compliance because it generates the counterfactual (control group) around the cut-off point, which shares similar characteristics with the treatment group.

In our study, the running variable is the entrance exam scores, which determine eligibility for vocational schools. To facilitate comparisons across different years and course categories, each with unique cut-off scores, we normalized the entrance exam scores by subtracting the cut-off score from each individual's actual score. This normalization process centers the running variable at zero in the FRDD, and the score of zero represents the cut-off point. We focus the analysis on the sample near the cut-off point. We use the Mean Square Error (MSE) optimal bandwidth choice to correct the misspecification error and variability (Calonico et al., 2020). Moreover, a higher-order polynomial is used to capture non-linear relationships in the running variable while maintaining the precision of the estimates.

Let Y be the outcomes of interest; VET be the enrolment of vocational education and training: Enexam be the entrance exam score; and c be the cut-off. ε is the distance from the cut-off. The identification strategy is defined as,

$$\frac{\lim\limits_{\varepsilon\uparrow 0} E[Y|Enexam=c+\varepsilon] - \lim\limits_{\varepsilon\downarrow 0} E[Y|Enexam=c+\varepsilon]}{\lim\limits_{\varepsilon\uparrow 0} E[VET|Enexam=c+\varepsilon] - \lim\limits_{\varepsilon\downarrow 0} E[VET|Enexam=c+\varepsilon]} = E[\ \beta i \mid \text{unit is complier, Enexam} = c] \quad (1)$$

A FRDD estimates the average causal estimates for the subpopulation called local average treatment effect (LATE) for compilers because of imperfect compliance. The identification in equation (1) is numerically equivalent to the Two-Stage Least Squares (2SLS) estimator within the system equations below.

First Stage equation:

$$VET_i = \gamma + Treat \times (\pi + g\ (Enexam_i - c)) + g(Enexam_i - c) + X_i\delta_{VET} + \varepsilon_i \quad (2)$$

Second Stage equation:

$$Y_i = \alpha + \beta\widehat{VET_i} + ⨍(Enexam_i - c) + X_i\delta_y + v_i \qquad (3)$$

Here Y_i represent the outcomes of interest for individual i; VET_i is the dummy for the vocational education and training participation; $Treat_i$ is the dummy for the assigned treatment status and takes the value of unity if an individual i's entrance exam score is above the cut-off; $Enexam_i$ is the entrance examination mark of the individual i; c is the cut-off entrance mark; and X_i captures the individual characteristics. Treat ($Enexam_i \geq c$), and ⨍ (.) and g(.) are the functions of the order of the polynomials; and v_i and ε_i are random error terms.

Outcomes of interest include the first employment, employment transition in mid-term (2022 and 2023), job designation, type of employment contract, sector of employment, the relevance of the employment, and monthly income (Table 5). To investigate the heterogeneous impact of VET, we will also estimate equations (1) and (2) separately for each type of program, such as a) APL, b) ARM, c) BC, d) EET, e) FBM, and f) ICM. Based on the heterogeneity impact results, the magnitude of the economic significance of each course is used to compare to identify the better course to improve the skills and generate employment opportunities among the courses.

Table 5

Description of Outcome Variables.

Outcome Variable	**Type**	**Description**
First Employment	Dummies	It takes value 1 if the individual "Mainly Engaged" at work after VET graduation.

Job Search Time	Dummies	It takes 1 if the individual found their first employment less than one year.
Employment Transition in 2022	Dummies	Employment transition in 2022 after five years of VET graduation (Same as first job, Promoted, Move to another job, Loss job). Captures career advancements and the impact of the economic crisis peak. Ex: It takes the value 1 if the individual moved to another job in 2022.
Employment Transition in 2023	Dummies	Change of employment in 2023 after six years of VET graduation. Ex: It takes the value 1 if the individual moved to another job in 2023.
Job Designation	Dummies	Employment position of the applicants. Whether they are at the Executive level, managerial level, or General Worker. The purpose is to measure how VET affects job designation. Ex: It takes 1 if the individual engages in Executive level job.
Type of Employment Contract	Dummies	This measures job security, capturing whether individuals are in permanent or temporary employment. Ex: It takes the value 1 if the individual has a long-term permanent employment, and 0 otherwise.
Sector of Employment	Dummies	In which sector individuals are engaged in work either the public sector, Private sector, or Self-employment. Ex: It takes 1 if the individual engages in public sector.
The Relevance	Dummies	It takes the value 1 if the individual is in a job aligned with their VET qualification. Measures job-matching, or how well vocational training aligns with the individual's actual job role.
Monthly Income	Dummies	It includes monthly wages and any other monthly income that is generated by using applicants' skills (entrepreneurship income) measured by Sri Lankan Currency. It has ranges (0-40,000 LKR, 40,001-80,000 LKR, above 80,000). Ex: It takes

1 if the individual's monthly income were 0-40,000 LKR bracket.

In the questionnaire, outcome variables were designed with selective answers, and the respondent chose one answer to ensure efficient data collection. This structured approach was particularly necessary as the survey was conducted via phone interviews, allowing respondents to provide answers quickly and accurately while minimizing interview time. To run FRDD regression, we generated separate dummies for each selective answer of the outcome variable and ran the FRDD separately. Therefore, all the outcome variables are dummies in this study.

5. Results and Discussion

Validity of Fuzzy RDD

This study tests the validity of the estimated causal effect of FRDD based on four identifying assumptions: (i) local continuity, (ii) first stage jump, (iii) exclusion restriction, and (iv) monotonicity. The continuity assumption explains that the distribution of running variables and predetermined covariates of the treated and control individuals must be continuous at the cutoff to ensure that the treatment assignment is as good as random (Lee and Lemiuex, 2010). There should not be a discontinuity (jump) at the cut-off besides a jump of treatment probability, which is entering VET. If there is any jump from other factors, it would be difficult to decide whether the differences in the outcomes around the cutoff are due to VET or due to other confounding factor(s). However, a drawback of the continuity assumption is that it has limited economic meaning. Therefore, continuity is implied by an alternative assumption which Lee and Lemieux (2010) refer to as "imprecise control" over the value of the assignment variable. As[4] continuity or imprecise control assumption is important and to check the validity of this assumption, the McCrary density test is performed. The results of the McCrary density test and density plot are shown in Appendix Table 4. In the McCrary

[4] Suppose there is complete control over the value of the assignment variable (entrance exam scores). In that case, it implies that individuals on one side of the threshold are systematically different from the individuals on the other side. This is because of self-selection. However, due to imprecise control, the abrupt changes in treatment status that occur at the cutoff result in a treatment assignment that is essentially random within a small neighborhood around the cutoff. Therefore, the observations around the cutoff are comparable in above and below the cutoff.

density test, the null hypothesis of "no manipulation" failed to be rejected. It indicates that the continuity assumption seems to be valid in this study.

The test of null treatment effect on predetermined covariates is performed using observations within the optimal bandwidth to provide additional evidence to support the continuity assumption (no manipulation). This test is specifically used to check if the treatment status had an effect on predetermined or baseline covariates. To ensure the validity of the continuity assumption, there should not be systematic differences between the predetermined covariates of the treatment group and the control group at the cutoff. According to the results in Table 5, there is no systematic difference between the treatment group and control group at the cut-off on predetermined covariates (baseline covariates) in the overall analysis. This test was performed for the heterogeneity analysis as well, and the results showed there were no systematic differences between the treatment and control groups in APL, BC, and FBM. There were some minor differences between genders in ARM and EET, and age in ICM. However, the fuzzy RDD estimates remained qualitatively unchanged after covariate adjustment.

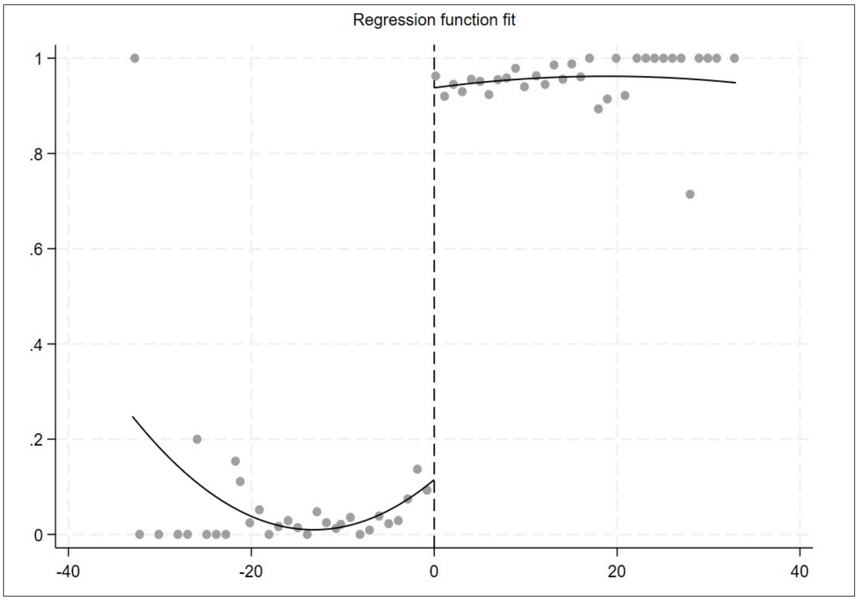
Table 6

Test of Null Treatment Effect on Pre-determined Covariates for Overall Analysis.

Variable	Mean of Treated	Mean of Controls	Difference in Means	p-value	Number of Observation
Gender	0.5615	0.5398	0.0217	0.1367	4734
Age	28.5104	28.3799	0.1305	0.0553	4734
Marital status	0.4779	0.4838	-0.0059	0.6887	4734
Number of children	0.2183	0.1928	0.0255	0.0528	4734
Parental income	2.1045	2.1431	-0.0385	0.2153	4734
Education level	0.7341	0.7538	-0.0198	0.1222	4734
Household size	4.2849	4.2503	0.0346	0.2972	4734
Pre-professional course	0.3398	0.3246	0.0152	0.2708	4734
Pre-working experience	0.1964	0.2155	-0.0191	0.1074	4734

Second, the first stage assumption requires a discontinuity in the probability of entering VET at the cut-off. This assumption is satisfied if there is a statistically significant jump at the cut-off. According to the first-stage regression results in Figure 1, the first-stage relationship between the treatment variable (entering VET) and the running variable (entrance exam scores) is statistically significant at a 1 percent level of significance. We estimated the first stage for the heterogeneity analysis for each course, and the results are statistically significant.

Figure 1: First stage regression for overall



The third assumption is exclusion restriction. It indicates that crossing the cut-off affects the outcomes only through the treatment and there is no direct effect. A possibility of violation of this assumption emerges if crossing the cut-off is likely to affect outcomes. However, the cut-off value of the entrance exam score of VET is not used for any other institute or program. The VET institutions (Technical Colleges) in this study uniquely implement VET programs. Therefore, the exclusion restriction assumption appears to be plausible in our setting.

The fourth assumption is monotonicity. It assumes that the study is away from defiers. This assumption appears to be plausible in this study. Because "defiers" are the ones who do the exact opposite thing. For instance, having the entrance exam score above the cutoff does not enter VET while the below applicants do enter VET. However, it would be very strange, and in this study, the applicants with the entrance exam score above the cut-off are more likely to enter VET. Therefore, the defiers are likely to be very close to zero.

A. Overall Results

In the overall analysis, we pool the data from six-course categories of applicants to technical colleges between 2015 and2017. We assess labor market outcomes across three critical time points**:** first job outcomes (immediate post-graduation)**,** 2022 (the economic crisis peak**)**, and 2023 (post-crisis recovery). Outcomes include employment transitions, sectoral distribution, contract type, job designations, monthly income, and job relevance (job matching). Year-fixed effects are applied to control for time-specific unobservable factors. Standard errors are clustered by year.

Table 7 shows the effect of VET on first employment (immediately after graduation). VET significantly improved immediate employment engagement, with a 5.9 percentage points increase in the likelihood of being "Mainly Engaged" at work. This indicates the program's effectiveness in facilitating labor market entry for graduates. However, there was no significant effect on job search durations of less than one year, suggesting some graduates experienced delays in securing their first positions. In terms of employment sectors, no notable changes were observed. The type of employment contractual outcomes revealed no significant effects immediately after graduation, although a downward trend was seen for long-term permanent jobs (-11.2 percentage points) and a upward trend for temporary employment (+14.6 percentage points). Job designations also showed no significant effect, although there was a modes positive trend in general worker positions (+4.7 percentage points). With respect to monthly income, the most notable and statistically significant increase was within the lowest income bracket (0–40,000 LKR), which rose by 9.8 percentage points. This suggests that while VET improves employability, it often leads to lower-paying positions rather than mid- or high-income roles. In terms of job relevance (job matching),"Related" roles showed no significant improvement, reflecting no significant alignment between training and job opportunities in their first employment.

Table 8 above shows the effect of VET in 2022. The year 2022 was considered the peak year of the economic recession in Sri Lanka because of energy shortages, spread of COVID-19, and riots all over the country. This period was characterized by high job mobility among VET graduates. Vocational graduates were less likely to remain in their first jobs (-26.4 percentage points) but showed a notable increase in moving to other jobs by 42.2 percentage points. However, other forms of job transitions, such as promotions, did not show significant change. Self-employment continued to rise significantly by 2.9 percentage points, reflecting adaptive strategies during the crisis. Temporary contracts showed a slight increase of 7.88 percentage points, while long-term permanent contracts remained negative. The rise in self-employment appeared to support an increase in executive roles, with a significant positive effect of 4.56 percentage points. It showed no significant gain in monthly income for higher income brackets after five years of graduation, suggesting that the economic crisis had a dampening effect on earning potential, even nearly five years post-graduation. In terms of job relevance, the share of “Related” jobs did not increase significantly, underlining a continued misalignment between vocational training and real-world labor market needs, especially in times of economic turbulence.

Labor Market Outcomes

First Employment (Immediately after graduation)

Table 7 : *The Impact of VET on First Employment.*

Variables	Engaged in work	Job search time		Employment status		Employment contract types			Job designation			Monthly income			Relevance
	Mainly engaged	Less than 1 year	More than 1 year	Wage employee	Self-employment	Long term permanent	Long term contract	Temporary	Executive	Managerial Level	General worker	0-40000	40001-80000	Above 80000	Related
Rd estimate	0.059***	-0.001	0.068	0.047	0.023	-0.113	0.076	0.146	0.009	0.007	0.048	0.098**	-0.014	0.005	0.017
	(0.016)	(0.043)	(0.072)	(0.043)	(0.027)	(0.137)	(0.087)	(0.114)	(0.023)	(0.005)	(0.037)	(0.049)	(0.030)	(0.012)	(0.095)
Control means	0.907	0.767	0.118	0.852	0.057	0.435	0.147	0.057	0.054	0.002	0.854	0.779	0.119	0.012	0.502
Number of observations	2449	3033	3225	2186	2700	2688	2449	2664	2925	1972	2499	2558	2668	2499	2755

2022: Economic Crisis Peak

Table 8 : *The Impact of VET in the Economic Crisis Peak Year.*

Variables	Employment transition				Employment status		Employment contract types			Job designation			Monthly income			Relevance
	Same as the first job	Promoted	Move to another job	Loss job	Wage employee	Self-employment	Long-term permanent	Long-term contract	Temporary	Executive	Managerial level	General worker	0-40000	40001-80000	Above 80000	Related
Rd estimate	-0.264**	-0.019	0.422***	0.024	0.036	0.029**	-0.037	0.070	0.079*	0.046**	-0.007	0.109	0.096	-0.024	-0.026	0.058
	(0.091)	(0.014)	(0.088)	(0.027)	(0.052)	(0.011)	(0.105)	(0.050)	(0.042)	(0.014)	(0.082)	(0.101)	(0.121)	(0.153)	(0.028)	(0.054)
Control means	0.355	0.013	0.165	0.061	0.598	0.019	0.427	0.096	0.093	0.068	0.153	0.453	0.351	0.293	0.050	0.378
Number of observations	2389	2810	2021	3033	1815	2260	2389	2233	2810	3117	2688	2774	2429	2688	2605	2796

2023: Post-Crisis Year

Table 9 : *The Impact of VET in the Post-Crisis Year.*

Variables	Employment transition					Employment status		Employment contract types			Job designation			Monthly income			Relevance
	Same as the first job	Same as the 2022	Promoted	Start a new job	Loss job	Wage-employment	Self-employment	Long-term permanent	Long-term contract	Temporary	Executive	Managerial level	General worker	0-40000	40001-80000	Above 80000	Related
Rd estimate	-0.213**	0.236***	-0.010	-0.142**	0.073**	0.074	0.018	-0.102	0.020	0.031	-0.066	-0.013	0.003	0.034	-0.042	0.051	-0.049
	(0.066)	(0.049)	(0.016)	(0.068)	(0.032)	(0.057)	(0.019)	(0.070)	(0.031)	(0.052)	(0.043)	(0.102)	(0.036)	(0.071)	(0.040)	(0.068)	(0.080)
Control means	0.259	0.117	0.006	0.280	0.050	0.653	0.094	0.455	0.116	0.095	0.109	0.228	0.435	0.368	0.356	0.066	0.386
Number of observations	2688	1972	2952	2796	3000	2916	2260	2925	2233	2916	2343	2233	2925	3016	2688	2429	3238

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9 presents the results of the effect in 2023, and this is the post-crisis year from the economic recession. In the post-crisis year of 2023, the results highlight the nuanced and evolving impact of vocational education on youth labor market outcomes. Vocational graduates show significant mobility, as they are less likely to remain in their first job (-21.3 percentage points) yet display increased stability in jobs held since 2022 by 23.6 percentage points. This suggests a gradual consolidation of employment post-crisis. However, it also showed significant job losses by 7.2 percentage points, suggesting that vocational graduates were not fully recovered. Moreover, there is limited evidence of upward mobility, with no significant impact on promotions.

Notably, the positive impact of self-employment observed in 2022 had disappeared by 2023, implying that many small or self-initiated ventures were not sustained beyond the crisis period. Even after six years, no significant effects were observed regarding employment contract types. The persistent negative trend in long-term permanent contracts underscores a key limitation of the current VET system in securing stable, long-term employment for graduates. Similarly, the earlier positive trend in executive-level positions—driven in part by self-employment—had faded, further reflecting the decline in entrepreneurial activity post-crisis. Income levels also showed no significant improvement, particularly within middle- and higher-income brackets, highlighting continued challenges in progressing beyond low-wage employment. A critical area of concern remains job relevance. The lack of significant improvement in securing "Related" jobs suggests ongoing misalignment between vocational training and actual labor market demands, even in the long-term after the graduation.

B. Heterogeneity Analysis

We have conducted a heterogeneity analysis for each course in first employment, 2022, and 2023 to identify the impact of different VET courses on labor market outcomes. We estimated each using the same outcomes of the previous section. For easy of gravity, here we discuss only major findings. Full estimation results are presented in Appendix Table from 1 to 4.

Table 10 shows the results for first employment for each course. The results of heterogeneity analysis indicate that VET had a significant positive impact on employment engagement immediately after graduation only for FBM with a 30.4 percentage point. We find no significant effect of job search duration less than one year after vocational graduation for all course categories. However, APL and BC graduates were significantly more likely to spent more than one year to find their first employment by 14.5 and 6.3 percentage points respectively, suggesting prolonged job search periods among VET graduates. In terms of sectoral distribution, only FBM graduates were significantly more likely to enter the private sector (+43.0 percentage points), while other course categories showed no notable sectoral trends. Long-term permanent employment was secured only by APL graduates, whereas ARM graduates were more likely to enter long-term contract employment. Regarding job roles, General Worker positions dominated, with FBM graduates by 58.4 percentage points and ARM graduates by 16.1 percentage points. Notably, BC graduates saw a significant increase in Executive positions by 9.1 percentage points. Finally, monthly income outcomes were concerning, as ARM and FBM graduates were more likely to earn within the lowest income bracket (0–40,000 LKR), highlighting potential wage stagnation for vocational graduates.

Table 10: Heterogeneity Results- First Employment

Course category	Variables	Engaged in work	Job search time	Employment status		Employment contract type		Job designation		Monthly income	Relevance
		Mainly engaged	More than 1 year	Wage employee	Self-employment	Long-term permanent	Long-term contract	Executive	General worker	0-40000	Related
Agriculture Plantation & Livestock (APL)	RD Estimate	0.249 (0.543)	0.145* (0.085)	-0.063 (0.272)	0.347 (0.262)	0.428*** (0.093)	-0.408 (0.376)	0.347 (0.261)	-0.063 (0.271)	0.401 (0.413)	-0.404 (0.340)
	Observations	112	31	115	160	82	89	82	115	93	82
Automobile Repair and Maintenance (ARM)	RD Estimate	0.131 (0.265)	-0.064 (0.415)	0.167** (0.088)	-0.013 (0.050)	-0.253 (0.236)	0.231** (0.094)	-0.032 (0.042)	0.161* (0.095)	0.246*** (0.049)	0.268 (0.294)
	Observations	202	271	244	654	251	153	167	242	218	184
Building & Construction (BC)	RD Estimate	-0.050 (0.036)	0.063** (0.031)	-0.051 (0.057)	0.062 (0.044)	-0.179 (0.171)	0.066 (0.081)	0.092** (0.042)	-0.046 (0.056)	0.002 (0.057)	-0.082 (0.205)
	Observations	804	1010	1170	1897	1434	1346	855	1170	1322	1123
Finance Banking & Management (FBM)	RD Estimate	0.304*** (0.065)	0.158 (0.236)	0.534*** (0.136)	-0.078 (0.107)	0.176 (0.126)	0.062 (0.081)	-0.105 (0.107)	0.585*** (0.170)	0.321*** (0.069)	0.294 (0.307)
	Observations	303	295	255	453	221	280	287	186	285	329

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Heterogeneity Results-2022 (Economic Crisis Year)

Course category	Variables	Employment transition			Employment status		Employment contract type			Job designation		Monthly income		Relevance
		Promoted	Move to another job	Loss job	Wage employee	Self-employment	Long-term permanent	Long-term contract	Temporary	Executive	Managerial level	0-40000	Above 80000	Related
Agriculture Plantation & Livestock (APL)	RD Estimate	-0.033	-0.624	0.088	-0.386***	0.099	-0.839	0.033	-0.102	0.246**	-0.394	-0.049	-0.444	-0.288
		(0.013)	(0.424)	(0.109)	(0.135)	(0.105)	(0.889)	(0.065)	(0.295)	(0.123)	(0.436)	(0.533)	(0.165)	(0.866)
	Observations	105	69	122	53	160	96	73	105	79	67	77	87	82
Automobile Repair and Maintenance (ARM)	RD Estimate	0.058*	0.441***	0.049*	0.020	0.196*	0.008	0.220**	-0.027	-0.047	0.214	-0.017	0.218	0.064
		(0.034)	(0.138)	(0.025)	(0.195)	(0.118)	(0.358)	(0.083)	(0.035)	(0.066)	(0.135)	(0.453)	(0.168)	(0.748)
	Observations	190	161	201	270	654	181	154	218	654	119	228	138	136
Building & Construction (BC)	RD Estimate	-0.032	0.369***	-0.013	0.141*	0.040*	-0.031	0.022	0.044	0.073***	0.014	0.067	0.003	0.066
		(0.022)	(0.079)	(0.027)	(0.079)	(0.021)	(0.109)	(0.056)	(0.062)	(0.019)	(0.033)	(0.113)	(0.030)	(0.168)
	Observations	1262	1170	1299	901	1897	909	1168	1047	855	1234	858	952	1342
Electrical, Electronics & Telecommunic ation (EET)	RD Estimate	-0.115	0.884***	0.060	0.699*	0.225***	0.168**	0.104	0.232***	-0.056	0.127	0.615	0.026	0.079
		(0.167)	(0.330)	(0.065)	(0.417)	(0.049)	(0.072)	(0.148)	(0.081)	(0.228)	(0.433)	(0.658)	(0.206)	(0.279)
	Observations	381	176	387	230	556	215	242	317	252	216	341	329	205
Finance Banking & Management (FBM)	RD Estimate	0.028	0.415***	0.075	0.208	-0.037	0.436	0.139***	0.020	-0.131	0.462***	0.251***	0.137***	0.336
		(0.028)	(0.094)	(0.239)	(0.133)	(0.033)	(0.285)	(0.046)	(0.255)	(0.042)	(0.135)	(0.058)	(0.049)	(0.289)
	Observations	292	290	279	286	453	265	240	254	331	265	273	221	340
Information Communicatio n & Multimedia (ICM)	RD Estimate	0.009	0.233**	0.028	-0.026	0.026	-0.078	0.042	0.085**	0.086	-0.126	0.088	-0.046	0.133
		(0.019)	(0.111)	(0.057)	(0.157)	(0.018)	(0.122)	(0.118)	(0.043)	(0.088)	(0.079)	(0.175)	(0.043)	(0.178)
	Observations	384	641	641	681	1119	661	500	511	500	610	581	796	546

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11 presents result for 2022, highlighting the significant job mobility among EET, ARM, FBM, BC, and ICM graduates. Vocational graduates were less likely to remain in their first jobs, shifting to new employment as an adaptive response to the economic crisis. However, promotions remained largely insignificant, with only a slight increase for ARM graduates after five years of graduation. We find Self-employment rose significantly for EET graduates and was marginally significant for ARM and BC graduates. Private sector employment significantly increased for EET and FBM graduates, indicating a shift in employment sectors during the crisis. The economic downturn eroded job security, with permanent employment gains for APL graduates disappearing, likely due to temporary layoffs and increased job switching. Conversely, EET graduates experienced an improvement in permanent employment. FRM graduates shifted toward contract-based roles, while ICM graduates were more likely to hold temporary jobs.

Shifts in job designation were evident, with APL and BC graduates moving into executive roles—largely through self-employment investments. FBM graduates progressed into managerial roles, indicating upward mobility despite the crisis. Income effects were mixed: FBM graduates experienced both high- and low-income outcomes, reflecting growing inequality and instability. Other groups (APL, ARM, BC, EET, and ICM) saw no significant income changes even five years post-graduation. Many VET graduates appeared to accept jobs outside their field of training, likely due to job mismatches and economic uncertainty.

Finally, Table 12 presents the results for 2023 (Post-Crisis Year). The findings indicate that vocational graduates in ARM, EET, FBM, and ICM remained in the same jobs as in 2022, suggesting reduced job mobility across most course categories. Promotion rates remained limited, highlighting persistent barriers to career progression among NVQ Level 4 graduates—likely stemming from prior job instability and insufficient qualifications for advancement. Job losses were particularly severe among BC graduates, reflecting the downturn in the construction sector, where numerous projects were halted due to debt and foreign reserve shortages. Notably, the self-employment gains observed in 2022 (for BC and EET graduates) dissipated in 2023, suggesting a decline in entrepreneurial activity in the post-crisis period.

Table 12- Heterogeneity Results- 2023 (Post-Crisis Year)

Course category	Variable	Employment transition				Employment status		Employment contract type			Job designation		Monthly income		Relevance
		Same as The 2022	Promoted	Start a new job	Loss job	Wage employee	Self-employment	Long-term permanent	Long-term contract	Temporary	Executive	Managerial level	0-40000	Above 80000	Related
Agriculture Plantation & Livestock (APL)	RD Estimate	-0.134	-0.019	0.601**	-0.573	0.039	0.407	-0.786	0.297	0.089	0.246	-	0.563*	-0.221	-0.467
		(0.356)	(0.039)	(0.277)	(0.553)	(1.789)	(0.250)	(1.703)	(0.258)	(0.563)	(0.540)		(0.330)	(0.626)	(1.196)
	Observations	89	85	94	69	97	160	102	79	91	89	160	80	89	74
Automobile Repair and Maintenance (ARM)	RD Estimate	0.287**	-	-0.037	-0.062	-0.302***	-0.021	-0.161	-0.042	-0.208	-0.081	0.247	-0.530	-0.033	0.349
		(0.113)		(0.009)	(0.084)	(0.122)	(0.202)	(0.229)	(0.077)	(0.263)	(0.080)	(0.266)	(0.171)	(0.063)	(0.314)
	Observations	198	330	138	235	224	654	212	138	236	138	224	235	246	214
Building & Construction (BC)	RD Estimate	0.151	-0.013	-0.171	0.141**	-0.079	-0.024	-0.167	0.003	0.027	-0.082	-0.004	-0.125	-0.023	-0.255
		(0.095)	(0.025)	(0.116)	(0.039)	(0.094)	(0.024)	(0.108)	(0.039)	(0.061)	(0.096)	(0.159)	(0.148)	(0.087)	(0.196)
	Observations	1234	914	1305	1104	967	1897	967	858	1184	901	989	1050	1089	1031
Electrical, Electronics & Telecommunication (EET)	RD Estimate	0.522***	-0.052	-0.365	-0.006	0.445***	-0.286	-0.285	0.272*	0.182**	-0.264	-0.243	0.569	0.056	-0.064
		(0.185)	(0.097)	(0.213)	(0.082)	(0.216)	(0.156)	(0.387)	(0.157)	(0.080)	(0.169)	(0.201)	(0.614)	(0.228)	(0.299)
	Observations	290	306	215	264	274	556	338	252	295	252	234	317	329	215
Finance Banking & Management (FBM)	RD Estimate	0.383***	0.004	-0.102	0.156	0.206	-0.258	0.590***	-0.242	0.010	-0.271	0.304**	-0.114	-0.036	0.320
		(0.059)	(0.036)	(0.071)	(0.148)	(0.272)	(0.078)	(0.135)	(0.107)	(0.205)	(0.163)	(0.123)	(0.137)	(0.072)	(0.232)
	Observations	271	306	189	221	300	453	271	271	271	203	233	273	263	329
Information Communication & Multimedia (ICM)	RD Estimate	0.269**	0.028*	-0.170	-0.043	0.128	0.105	-0.164	-0.053	-0.078	0.087***	-0.272	0.087	0.178***	0.141
		(0.125)	(0.015)	(0.149)	(0.122)	(0.215)	(0.080)	(0.214)	(0.056)	(0.090)	(0.031)	(0.086)	(0.119)	(0.021)	(0.156)
	Observations	547	261	671	435	605	1119	577	681	511	575	478	529	577	575

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Long-term permanent employment improved only for FBM graduates, but job security remained uncertain for most vocational graduates. Many still rely on contract and temporary positions, leaving them vulnerable to external shocks. FBM graduates saw continued managerial-level job stability, though at a lower rate than in 2022. Monthly income outcomes remained mixed, with APL graduates marginally more likely to fall into the lowest income bracket, while ICM graduates saw significant improvements in the highest income bracket. However, most vocational graduates experienced no considerable income gains, suggesting earnings remained constrained post-crisis. None of the course categories showed significant improvements in job relevance, indicating that vocational graduates continued to struggle with job-skills alignment even six years after graduation.

Overall, the analysis revealed that while Vocational Education and Training (VET) in Sri Lanka facilitates early labor market entry with a 5.9 percentage point increase in the likelihood of being engaged in employment this benefit does not extend into long-term employment quality. Despite increased job participation immediately after graduation, the majority of VET graduates are absorbed into low-paying, temporary or contract-based positions. Moreover, the findings consistently showed that VET did not significantly improve access to long-term permanent jobs, nor did it lead to upward income mobility or a strong alignment between training and job relevance across the observed timeframes.

The lack of significance results in many labor market outcomes does not necessarily suggest that VET is ineffective but rather highlights key structural labor market challenges that limit the benefits of vocational training. Since the enrolment to the vocational schools' delays labor market entry for the treatment group, control individuals accumulate more work experience, potentially making them more competitive in the job market. This could explain the reasons why vocational graduates do not exhibit significant advantages in first employment outcomes. Moreover, the economic crisis disrupted expected labor market trajectories. Frequent job mobility, lack of promotions, persistent temporary employment, and stagnant monthly income growth and executive roles suggest that vocational graduates struggled to secure stable career paths. This, combined with job mismatching, explains the widespread insignificance in key employment indicators. Therefore, vocational graduates faced barriers in securing stable employment and career progression, indicating the need for stronger industry linkages and policy support.

7. Conclusion

This study uses a fuzzy regression discontinuity design to estimate the causal impact of vocational education and training (VET) on youth labor market outcomes in Sri Lanka. While VET significantly improves immediate employment outcomes, long-term effects, such as access to permanent contracts, income mobility, and job relevance, remain limited. These findings highlight the need for a multifaceted policy response to enhance the effectiveness of VET as a sustainable employment pathway.

First, curriculum reforms must be aligned more closely with labor market needs. The persistent mismatch between training and job relevance underscores the importance of involving industry advisory boards in curriculum development to ensure alignment with employer demand (ILO, 2022). Second, dual-training models that combine classroom learning with structured workplace experience should be institutionalized to improve long-term employability and facilitate access to secure jobs. Third, introducing modular upskilling pathways can support the development of both technical and managerial competencies, enabling graduates to advance their careers and increase their earnings. Fourth, targeted support for youth entrepreneurship, including seed funding, mentoring, and incubation programs—is necessary to make self-employment ventures more resilient during economic shocks. Ultimately, establishing a national VET graduate tracking system would enable policymakers to monitor long-term outcomes, identify gaps, and assess the effectiveness of interventions.

The heterogeneity analysis further emphasizes the need for course-specific reforms. Graduates in Agriculture and Building and construction often experience delayed employment and low income, highlighting the importance of modernizing curricula by integrating agribusiness, green construction practices, and digital tools to enhance employability. The streams such as Finance and Electrical showed favourable employment and some career outcomes, justifying continued investment. For ICT-related fields, however, basic training must be upgraded to include advanced digital competencies such as coding, web development, and data analytics (Hayashi, 2019), ensuring alignment with the evolving demands of the tech sector.

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Appendix

Table A1: Heterogeneity Analysis First Employment

Outcomes		Engaged In Work	Job Search Time		Employment status		Employment contract type			Job designation			Monthly income			Relevance
		Mainly Engaged	Less Than 1 Year	More Than 1 Year	Wage Employee	Self-Employment	Long-Term Permanent	Long-Term Contract	Temporary	Executive	Managerial Level	General Worker	0-40000	40001-80000	Above 80000	Related
Agriculture Plantation & Livestock	RD Estimate	0.250	0.100	0.146*	-0.063	0.348	0.428***	-0.408	0.263	0.348	-	-0.063	0.401	-0.429	-0.007	-0.404
		(0.543)	(0.754)	(0.085)	(0.272)	(0.262)	(0.093)	(0.376)	(0.643)	(0.262)		(0.271)	(0.413)	(0.429)	(0.015)	(0.340)
	Observations	112	89	31	115	82	82	89	41	82	160	115	93	94	91	82
Automobile Repair and Maintenance	RD Estimate	0.131	0.425	-0.064	0.168*	-0.013	-0.253	0.231**	0.438	-0.032	0.011	0.161*	0.246***	-0.058	0.044	0.269
		(0.265)	(0.385)	(0.415)	(0.088)	(0.050)	(0.236)	(0.094)	(0.389)	(0.042)	(0.009)	(0.095)	(0.049)	(0.046)	(0.060)	(0.294)
	Observations	202	170	271	242	167	251	153	259	167	359	242	218	167	161	184
Building & Construction	RD Estimate	-0.050	-0.100***	0.063**	-0.051	0.062	-0.180	0.066	-0.052	0.092**	0.011*	-0.046	0.003	-0.094*	0.042	-0.082
		(0.036)	(0.033)	(0.031)	(0.057)	(0.044)	(0.171)	(0.081)	(0.144)	(0.042)	(0.007)	(0.056)	(0.057)	(0.050)	(0.027)	(0.205)
	Observations	804	842	1010	1170	858	1434	1346	1010	855	858	1170	1322	913	855	1123
Electrical, Electronics & Telecommunication	RD Estimate	0.093	0.223	-0.009	0.270	-0.104	-0.191	0.211	0.125	-0.110	0.001	0.270	0.204	0.122	-0.145	0.283
		(0.182)	(0.215)	(0.195)	(0.387)	(0.181)	(0.257)	(0.132)	(0.234)	(0.164)	(0.016)	(0.387)	(0.160)	(0.209)	(0.108)	(0.322)
	Observations	319	267	295	303	295	259	249	273	258	440	303	319	293	444	303
Finance Banking & Management	RD Estimate	0.304***	0.123	0.158	0.534***	-0.079	0.176	0.062	0.399	-0.105	-	0.585***	0.321***	-0.125	-0.035	0.294
		(0.065)	(0.217)	(0.236)	(0.136)	(0.107)	(0.126)	(0.081)	(0.266)	(0.107)		(0.170)	(0.069)	(0.119)	(0.036)	(0.307)
	Observations	303	279	295	255	314	221	280	287	287	452	186	285	245	254	329
Information Communication & Multimedia	RD Estimate	-0.089	-0.069	-0.038	-0.075	0.090	0.036	-0.068	-0.107***	0.053	-	-0.062	-0.320***	0.122	0.023	0.176
		(0.138)	(0.091)	(0.066)	(0.131)	(0.138)	(0.192)	(0.195)	(0.032)	(0.112)		(0.128)	(0.079)	(0.134)	(0.027)	(0.137)
	Observations	612	745	577	671	481	671	546	671	384	610	671	610	648	716	500

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Heterogeneity Analysis 2022 Employment

		Employment Transition				Employment status		Employment contract type			Job Designation			Monthly Income			Relevance
Outcomes		Same As the First Job	Promoted	Move To Another Job	Loss Job	Wage Employee	Self-Employment	Long-Term Permanent	Long-Term Contract	Temporary	Executive	Managerial Level	General Worker	0-40000	40001-80000	Above 80000	Related
Agriculture Plantation & Livestock	RD Estimate	-0.123*	-0.033***	-0.624	0.088	1.061***	0.100	-0.839	0.033	-0.102	0.247**	-0.394	0.021	-0.049	-0.188	-0.444***	-0.288
		(0.074)	(0.013)	(0.424)	(0.110)	(0.270)	(0.106)	(0.889)	(0.065)	(0.295)	(0.123)	(0.436)	(0.117)	(0.533)	(0.657)	(0.165)	(0.866)
	Observations	75	105	69	122	53	86	96	73	105	79	67	91	77	94	87	82
Automobile Repair and Maintenance	RD Estimate	-0.165	0.059*	0.441***	0.049*	0.020	0.196	0.008	0.220***	-0.027	-0.048	0.215	0.151	-0.017	-0.062	0.218	0.065
		(0.210)	(0.034)	(0.138)	(0.025)	(0.195)	(0.119)	(0.358)	(0.083)	(0.035)	(0.066)	(0.135)	(0.374)	(0.453)	(0.129)	(0.168)	(0.748)
	Observations	202	190	161	201	270	202	181	154	218	119	201	228	202	138	208	136
Building & Construction	RD Estimate	-0.231***	-0.033	0.370***	-0.013	0.141*	0.040*	-0.031	0.023	0.045	0.073***	0.014	0.103	0.067	0.115	0.003	0.066
		(0.082)	(0.022)	(0.079)	(0.028)	(0.080)	(0.021)	(0.109)	(0.056)	(0.062)	(0.020)	(0.034)	(0.162)	(0.113)	(0.098)	(0.030)	(0.168)
	Observations	901	1262	1170	1299	901	746	909	1168	1047	855	1234	1050	858	952	952	1342
Electrical, Electronics & Telecommunication	RD Estimate	-0.422*	-0.115	0.884	0.060	0.700	0.225	0.168	0.104	0.232	-0.056	0.127	0.501	0.615	-0.075	0.026	0.080
		(0.256)	(0.167)	(0.331)	(0.065)	(0.417)	(0.049)	(0.072)	(0.148)	(0.081)	(0.228)	(0.433)	(0.465)	(0.658)	(0.459)	(0.206)	(0.279)
	Observations	328	381	176	387	230	229	215	242	317	252	216	220	341	215	329	205
Finance Banking & Management	RD Estimate	-0.267***	0.029	0.415***	0.076	0.209	-0.038	0.436	0.140***	0.020	-0.131***	0.462***	0.147	0.251***	0.067	0.137***	0.336
		(0.046)	(0.028)	(0.094)	(0.240)	(0.133)	(0.033)	(0.285)	(0.046)	(0.255)	(0.042)	(0.135)	(0.120)	(0.058)	(0.140)	(0.049)	(0.289)
	Observations	353	292	290	279	286	317	265	240	234	331	265	189	273	292	221	340
Information Communication & Multimedia	RD Estimate	-0.108	0.010	0.233*	0.029	-0.026	0.026	-0.079	0.042	0.085**	0.086	-0.126	0.042	0.089	-0.276	-0.046	0.133
		(0.172)	(0.020)	(0.111)	(0.057)	(0.157)	(0.018)	(0.122)	(0.118)	(0.043)	(0.088)	(0.080)	(0.136)	(0.175)	(0.297)	(0.043)	(0.179)
	Observations	681	384	641	641	681	813	661	500	511	500	610	641	581	435	796	546

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Heterogeneity Analysis 2023 Employment

Outcomes		Employment transition: Same as the first job	Employment transition: Same as the 2022	Employment transition: Promoted	Employment transition: Move to another job	Employment transition: Loss Job	Employment status: Wage Employee	Employment status: Self-Employment	Employment contract type: Long-Term Permanent	Employment contract type: Long-Term Contract	Employment contract type: Temporary	Job designation: Executive	Job designation: Managerial Level	Job designation: General Worker	Monthly income: 0-40000	Monthly income: 40001-80000	Monthly income: Above 80000	Relevance: Related
Agriculture Plantation & Livestock	RD Estimate	-0.237 (0.519)	-0.134 (0.356)	-0.020 (0.039)	0.601** (0.277)	-0.573 (0.553)	0.039 (1.789)	0.407 (0.250)	-0.786 (1.703)	0.297 (0.258)	0.089 (0.563)	0.246 (0.540)	-	0.475 (0.530)	0.563* (0.330)	-0.084 (0.287)	-0.222 (0.627)	-0.467 (1.196)
	Observations	86	89	85	94	69	97	103	102	79	91	89	-	107	80	99	89	74
Automobile Repair and Maintenance	RD Estimate	-0.139 (0.102)	0.287** (0.113)	- (-)	-0.037*** (0.009)	-0.062 (0.084)	-0.302** (0.122)	-0.021 (0.202)	-0.161 (0.229)	-0.042 (0.077)	-0.208 (0.263)	-0.081 (0.080)	0.247 (0.266)	-0.040 (0.268)	-0.530*** (0.171)	0.082 (0.181)	-0.033 (0.064)	0.349 (0.314)
	Observations	201	198	330	138	235	224	228	212	138	236	138	224	202	235	138	246	214
Building & Construction	RD Estimate	-0.305*** (0.058)	0.151 (0.095)	-0.013 (0.025)	-0.171 (0.116)	0.141*** (0.039)	-0.079 (0.094)	-0.024 (0.024)	-0.167 (0.108)	0.003 (0.040)	0.027 (0.061)	-0.082 (0.097)	-0.004 (0.160)	-0.034 (0.130)	-0.125 (0.148)	-0.089 (0.059)	-0.023 (0.087)	-0.255 (0.196)
	Observations	973	1234	914	1305	1104	967	797	967	858	1184	901	989	1147	1050	741	1089	1031
Electrical, Electronics & Telecommunication	RD Estimate	-0.332 (0.361)	0.522*** (0.186)	-0.052 (0.097)	-0.365 (0.213)	-0.006 (0.082)	0.445** (0.217)	-0.286** (0.156)	-0.286 (0.387)	0.272* (0.157)	0.182** (0.080)	-0.264 (0.169)	-0.243 (0.201)	0.307 (0.207)	0.570 (0.614)	-0.478 (0.424)	0.056 (0.228)	-0.064 (0.300)
	Observations	207	290	306	215	264	274	205	338	252	295	252	234	230	317	327	329	215
Finance Banking & Management	RD Estimate	-0.653* (0.396)	0.383*** (0.060)	0.004 (0.036)	-0.102 (0.071)	0.156 (0.149)	0.207 (0.272)	-0.258*** (0.078)	0.590*** (0.136)	-0.242** (0.107)	0.010 (0.205)	-0.271* (0.163)	0.304** (0.123)	0.010 (0.085)	-0.114 (0.137)	0.121 (0.187)	-0.036 (0.072)	0.320 (0.232)
	Observations	347	271	306	189	221	300	296	271	271	271	203	233	321	273	204	263	329
Information Communication & Multimedia	RD Estimate	-0.182 (0.137)	0.270** (0.125)	0.028* (0.016)	-0.170 (0.150)	-0.043 (0.122)	0.128 (0.215)	0.105 (0.080)	-0.164 (0.214)	-0.053 (0.057)	-0.078 (0.090)	0.087*** (0.031)	-0.272*** (0.086)	0.048 (0.156)	0.087 (0.119)	-0.112 (0.177)	0.178*** (0.022)	0.141 (0.156)
	Observations	661	547	261	671	435	605	652	577	681	511	575	478	692	529	371	577	575

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: FRDD Manipulation Test Results

Cut-off	T-Statistics	P-value	Kernel	BW method	Effective observations (Left)	Effective observations (Right)
Normalized exam score (0)	0.2188	0.8268	Triangular	Combination (comb)	2027	2621

Table A5: *Test of Null Treatment Effect on Pre-determined Covariates*

Variable	Mean of Treated	Mean of Controls	Difference in Means	p-value	Number of Observation
Gender	0.4314	0.4383	0.0068	0.3938	21,871
Age	26.4978	26.5148	0.0170	0.6698	21,871
Education level	0.7047	0.6967	-0.0080	0.2821	21,871

Overall Analysis

Employment - First Employment

Figure 1: Engaged in Work
(Mainly engaged)

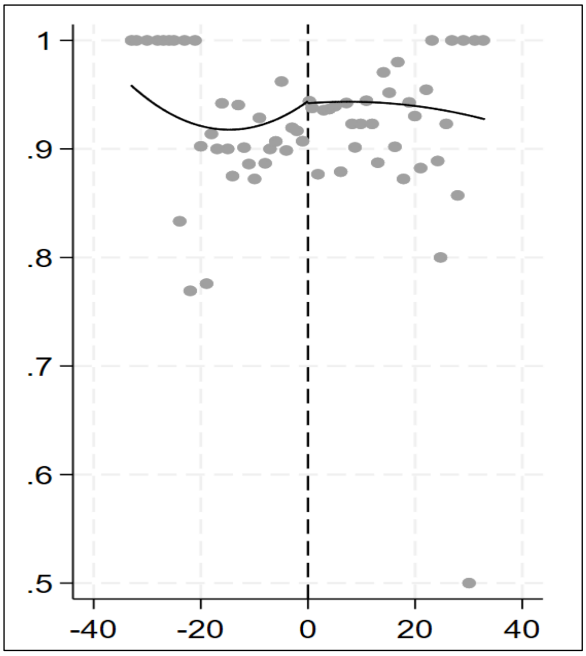
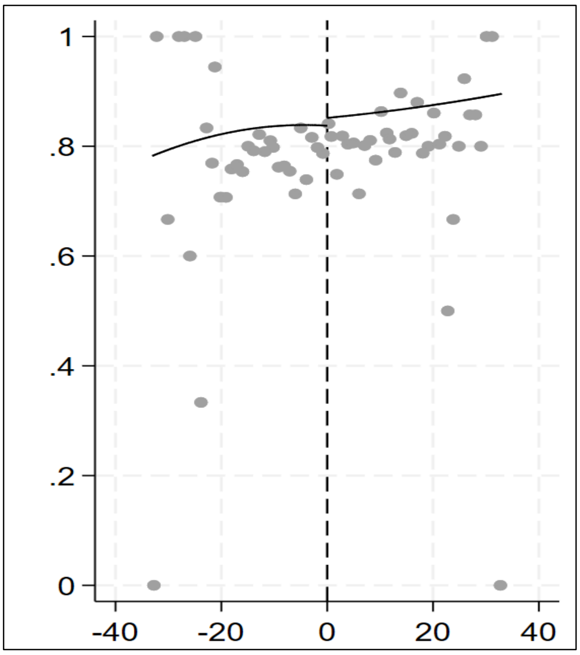


Figure 2: Monthly Income
(0-40000)



Employment - 2022

Figure 3: Employment transition
(Move to another job)

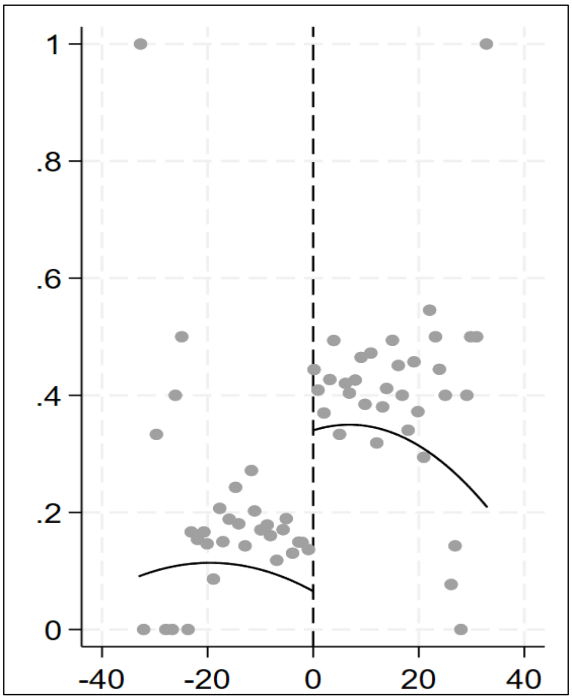


Figure 4: Employment Contracts
(Temporary Contract)

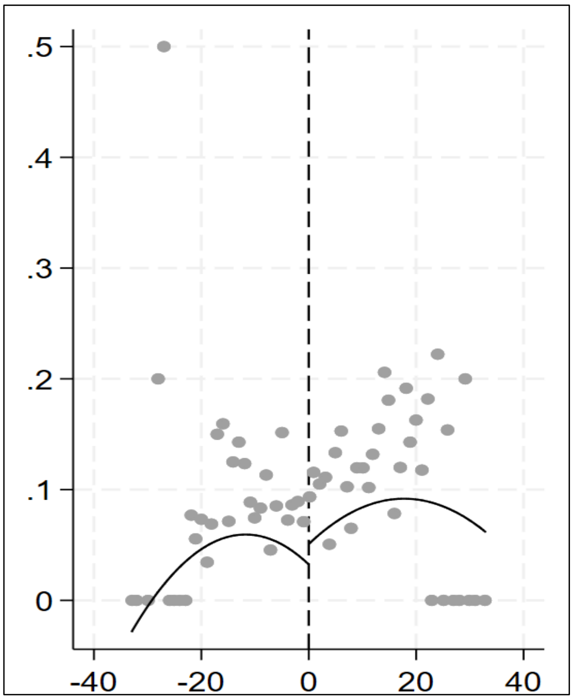
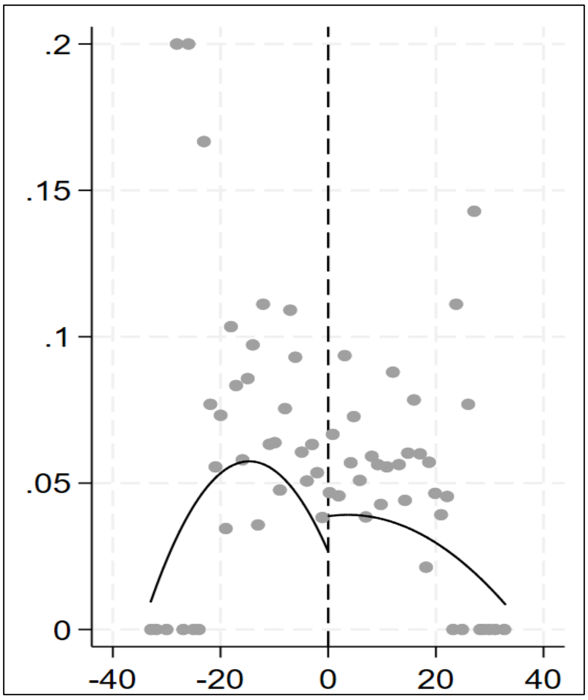


Figure 5: Job Designation
(Executive)



Employment – 2023

Figure 6: Employment transition
(Same as 2022)

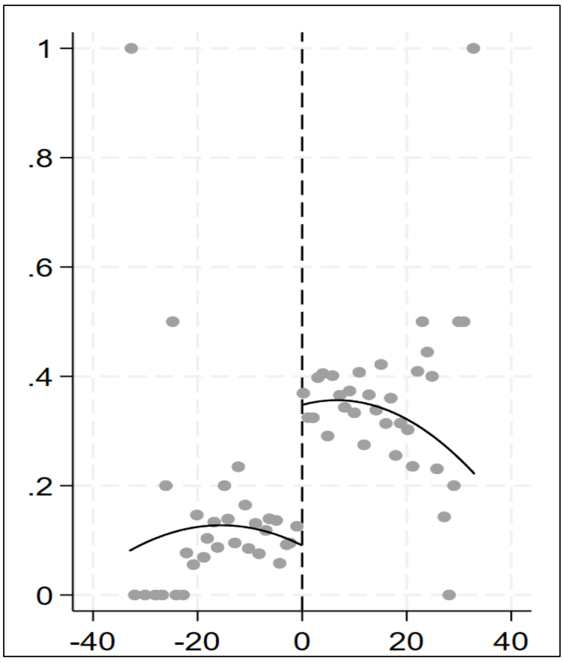


Figure 7: Employment transition
(Loss Job)