Economics Development Analysis Journal Vol. 13 (2) (2024)

Economics Development Analysis Journal

http://journal.unnes.ac.id/sju/index.php/edaj

Optimizing The *Program Kartu Prakerja* for Young Workers

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Article Information

History of Article
Received January 2024
Accepted March 2024
Pusblished May 2024

Keywords:
Active labour market policy, Program Kartu Prakerja, Youth, unemployment, earnings

Abstract

The Program Kartu Prakerja is a vital initiative in Indonesia to enhance job opportunities and quality, particularly for vulnerable individuals such as young workers. Many studies focus on unemployed individuals as research subjects. However, the real challenge is faced by the unemployed and those who are already employed. This paper investigates the program's effectiveness in enhancing employment opportunities for young workers by evaluating its impact on the probability of job retention and earnings. Using the August 2021 National Labour Force Survey (Sakernas) data, this study employs the Propensity Score Matching (PSM) method to compare the treatment group receiving the program with the control group not receiving the intervention. The findings show that the program had a significant negative impact on the probability of job retention for young participants, implying that some participants left their previous jobs in search of new ones. Another finding indicates that the program positively impacts earnings, although this impact was not statistically significant. These findings underscore the program's role as a strategic response to improving the labor market's functioning, which needs further optimization.

ISSN 2252-6560

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INTRODUCTION

Policymakers worldwide are developing effective strategies to increase employment opportunities and promote decent work in line with the Sustainable Development Goals. Various forms of government intervention in labor market policies, known as Active Labor Market Policies (ALMPs), have been implemented in several countries to actively address labor market challenges (McKenzie, 2017). ALMPs are government-funded interventions designed to improve labor market functioning. These policies aim to stimulate changes in labor demand and supply, preserve existing jobs, create new employment opportunities, and facilitate the reintegration of unemployed individuals into the labor force. ALMPs play crucial role in fostering inclusive economic development by enhancing employment opportunities for disadvantaged individuals (Ernst et al., 2022; Ingold & McGurk, 2023; Nordlund & Greve, 2018). They include various programs such as training, internships, financial incentives, and employment assistance (European Commission, 2023).

In Indonesia, the government has rolled out the *Program Kartu Prakerja* as part of its Active Labor Market Policies (ALMPs), which is expected to bridge educational and vocational training gaps in anticipation of future skill demands (APEC, 2021). Initiated in April 2020 through Presidential Regulation Number 36 of 2020, this program aims to enhance the skills and knowledge of the workforce in Indonesia, thereby increasing their productivity and competitiveness in the job market. Additionally, it aims to promote entrepreneurship among Indonesian citizens, creating more job opportunities in the country. The objective is pursued by opening registration to all Indonesian citizens aged at least 18 years and not currently pursuing formal education, both for the unemployed and individuals already employed (Job Creation Committee, 2022).

In its first year of implementation, the program provided 1,701 different types of training from 150 institutions across seven digital platforms. These training courses covered various skills, such as information technology, sales and marketing, administration, finance, and accounting. Additionally, the program offered post-training incentives totalling IDR2.4 million. Indonesian citizens received the program enthusiastically, with 43.8 million registering and 5.5 million becoming beneficiaries (Job Creation Committee, 2021). The program has proven successful, and the company is optimistic about its continuation in the following years, extending through 2024.

The policy has been implemented for a good reason. Indonesia faces a challenging employment landscape characterized by unemployment, wage disparities, and limited job opportunities. According to data from Statistics Indonesia (BPS), as of August 2021, the unemployment rate in Indonesia stood at 6.5%, with 9 million people being unemployed. The high unemployment rate among young people aged 15-24 is a significant concern, with around one-fifth of the youth labor force unemployed. The issue of youth unemployment in Indonesia extends beyond just the high unemployment rate; it also affects those who are already employed. Around 40% of young workers are underemployed, meaning they work fewer than standard working hours and seek additional employment opportunities (BPS-Statistics Indonesia, 2021).

Another issue in Indonesia's employment is the unequal income distribution among different age groups. Decent work involves productive work that offers a sufficient income, ensuring the well-being of workers and their families. Young people's average monthly net income is lower than other age groups. In 2019, in Indonesia, the average monthly net income for self-employed youth was about 23% lower than that of productive self-employed adults (aged 25-54). Similarly, young employees received wages about 34% lower than productive adult laborers.

Furthermore, in 2020-2021, the income and wage levels for workers in Indonesia declined, including for young workers (BPS-Statistics Indonesia, 2021). It is clear from the situation that the labor market conditions for young workforces are pretty different from those for adult workers in many ways. Young people tend to face a higher risk of unemployment and are more likely to work for low wages.

Some empirical studies have been conducted in different countries to analyze the impact of ALMPs on employment, such as off-the-job training. They concluded that ALMPs generally have a positive and statistically significant effect on increasing program participants' employment probability (Blázquez et al., 2019; Costabella, 2017; Destefanis et al., 2023; Ghirelli et al., 2019; Kantová & Arltová, 2020; Kruppe & Lang, 2018; Lindley et al., 2015; Speckesser et al., 2019; Wiśniewski, 2022; Zoellner et al., 2018).

Not only does ALMP increase employment opportunities, but it also has a positive impact on the income of program participants (Biewen et al., 2014; Burger et al., 2022; Dengler, 2019; Grunau & Lang, 2020; Lammers & Kok, 2021; Novella & Valencia, 2022; Vooren et al., 2022). Additionally, several other studies highlight that vulnerable groups such as the youth also benefit from this positive impact (Al Ayyubi et al., 2023; Escudero et al., 2019; Focacci, 2020; Kluve et al., 2019; Kruppe & Lang, 2018; Mourelo & Escudero, 2017; Pastore & Pompili, 2020).

However, McKenzie (2017) argues that policymakers in developing countries have not achieved the desired effectiveness of ALMPs. Additionally, Card et al. (2018) summarize that the overall effect of ALMPs varies among different groups, particularly noting that younger and older workers see less benefit on average. Moreover, Alegre et al. (2015), Bratti et al. (2022), Rotar (2021), and Dias et al. (2013) all suggest that any optimism about these policies should be tempered, as the programs do not have statistically significant positive impacts on unemployed young people. The effectiveness of ALMPs may differ depending on how the programs are designed and implemented, as indicated by the varying impacts in each country and for each observation group.

Within Indonesia, the *Program Kartu Prakerja* has demonstrated positive employment outcomes (J-PAL SEA, 2021; Presisi Indonesia, 2022). However, not all parts of the population have benefited equally from the program. Despite its successes, the country still grapples with high youth unemployment, impacting one-fifth of this age group. Furthermore, about 40% of young workers are underemployed. Indonesian young workers also encounter income disparities (BPS, 2021).

Analyzing the effectiveness of ALMPs is crucial for policymakers to make informed decisions and allocate resources efficiently. Understanding successful programs helps refine policies and develop targeted interventions. However, research on the effectiveness of the *Program Kartu Prakerja* is still limited, as the program was only implemented during the COVID-19 pandemic. Moreover, most studies focus on unemployed individuals, while the workforce that already has jobs also faces challenges. This research aims to analyze the impact of the policy program on the probability of retaining employment and the earnings of young participants who were employed while participating in the program activities.

This study employs the Propensity Score Matching (PSM) method to compare program participants with non-participants with similar characteristics. Our findings show that the program did not yield a positive significant difference in the probability of retaining employment and earnings between the intervention and comparison groups, indicating that some challenges still need to be addressed in the program's implementation. The research results can be used to evaluate the program's sustainability and effectiveness early.

The paper is structured into several sections, each delving into a specific aspect of the study. The next section is dedicated to research methods, which provide a clear understanding of the research design, such as the study scope, data collection methods, and analysis techniques used. Then, another section focuses on presenting the results and discussing the study. Finally, the last section summarizes the study's findings and conclusions succinctly. It briefly overviews the research problem, objectives, methodology, and main results. This section also highlights the study's limitations and provides recommendations for future research.

RESEARCH METHODS

The research encompasses individuals aged 18 to 24 from every district and city across Indonesia, specifically targeting those employed at the time of their registration for the *Program Kartu Prakerja.* The criteria for selecting participants align with the program's eligibility requirements, which include being an Indonesian citizen aged 17 and above, not being engaged in formal education, and being part of the workforce. These participants are then categorized into two groups: one that received the program benefits (treatment group) and another that did not (control group).

The study uses secondary data collected from the National Labor Force Survey (Sakernas) by BPS-Statistics Indonesia for August 2021. This data source and period were selected because they include recent questions about the program and meet the research sample criteria. Moreover, this survey had 3,602 respondents during the period, with 943 participants in the program and 2,659 not in the program, all meeting the research sample criteria. The year 2021 was chosen as the timeframe for the study, as it was considered a pivotal moment for Indonesia's post-COVID-19 recovery. This selection aligns with the study's objectives of providing stakeholders with early-stage evaluation tools for the program, which has been in place since the onset of the pandemic.

Table 1. Research Observations

Observation	Number of Observation
Program's Participants	943
Non-Participants	2,659
Total	3,602

Source: BPS-Indonesia, 2021 (Processed)

In this research, we classified the variables into three types: outcome variables, treatment variables, and covariate variables. The program's effectiveness is evaluated by comparing individuals who participate with a control group that does not receive the program's benefits. Thus, the treatment variable is defined as participation in the program. We control individual differences using covariate variables, including age, gender, residential area, education level, and prior work experience. Meanwhile, the primary outcome variables are the probability of retaining employment and earnings.

The analysis method used in this study is PSM, which constructs a statistical counterfactual by matching the characteristics of individuals in the treatment and control groups based on the covariate variables used (Rosenbaum & Rubin, 1983). This method allows the analysis results to be attributed to the treatment rather than any bias, as selection bias may arise when two individuals with identical characteristics have different chances of being treated (Khandker et al., 2009). This approach effectively addresses the bias issue by ensuring that the treatment and control groups are matched based on their characteristics (Caliendo & Kopeinig, 2008).

The stages for applying the PSM method in this research are as follows: First, Estimating Propensity Scores. This method creates a statistical comparison group based on observed characteristics to determine the likelihood of participating in the treatment. Participants are matched with nonparticipants based on this probability, known as a propensity score. The propensity score is calculated through a probit model, which treats enrollment in the program as the outcome variable, with all covariate variables serving as predictors. The formula for the propensity score is as follows:

$$Prob\ (treatment = 1|\mathrm{X}) = \beta_0 + \beta_i X_{ij} + \varepsilon_j \quad (1)$$

Here, X_{ij} refers to the *i*-th covariate variable, β_0 is the intercept, β_i is the slope for the i-th covariate, and ε_j is the residual for the *j*-th observation.

Second stage is defining the common support region. The common support region is defined by checking for an overlap in the propensity score distribution graph between the treatment and comparison groups. The equation indicates the balance $\hat{P}\ (\mathrm{X}\,|\mathrm{D} = 1) = \hat{P}\ (\mathrm{X}\,|\mathrm{D} =$

0), which denotes the similarity in the distribution of the treatment and control groups.

Third stage is Matching observations. To fulfil the conditional independence assumption, treated observational units can be matched with control observations with similar propensity scores. This matching ensures that the two groups have similar characteristics, and any differences observed are likely due to program participation. In this study, matching analysis is done using the nearest neighbour (NN) matching method, which pairs treatment group characteristics with the comparison group based on closest propensity scores.

The fourth stage is balancing diagnostics. Balancing tests are carried out using t-tests to determine if significant differences exist between the treatment and control groups regarding the utilized covariates, both before and after matching. This ensures that there is partial mean equality between the two groups. This is necessary to verify if the matched observations from the common support to reduce bias.

The fifth stage is estimating treatment effects. The primary analysis using this method aims to assess the impact of the intervention on the beneficiaries by measuring the Average Treatment Effect on The Treated (ATT), which is calculated as follows:

$$E(Y_{1i}|\, P(X), D_i = 1) - E(Y_{0i}|P(X), D_i = 0) \quad (2)$$

Where $Di \in \{0,1\}$ is a dummy variable for the treatment group, taking the value 1 if the individual is a program participant and 0 is a non-participant of the program. Y_j is the outcome variable, representing the probability of retaining employment and earnings. Y_{1j} is the expected outcome when the *j*-th individual is a program beneficiary (D_j = 1), and Y_{0j} is the expected outcome for a comparison individual based on the covariate X.

The last stages is checking results robustness. The estimated ATT value will be compared with other matching methods like radius and kernel to ensure robust estimation results. The outcomes produced by different matching techniques are consistently aligned, ensuring reliable results for drawing meaningful conclusions.

Table 2. Research Variables

Variables		Measurement
Probability of job retention	0:	Unemployed at survey period
	1:	Employed at survey period
Earnings		Rupiah per month (ratio scale)
Program Participation	0:	Non-participant
	1:	Participant
Age		Year (ratio scale)
Sex	0:	Female
	1:	Male
Residential area	0:	Rural
	1:	Urban
Education level	0:	Not completed in primary school
	1:	Elementary school
	2:	Middle school
	3:	High school
	4:	Diploma/bachelor/postgraduate
Job Experience	0:	Had no job experience
	1:	Had job experience

Source: BPS-Indonesia, 2021 (Processed)

Table 3. Descriptive Statistics

Variable	Non-Participant (Y=0)		Participant (Y=1)	
	Mean	**Std. Dev**	**Mean**	**Std. Dev**
Prob. job retention	0.7898	0.4075	0.7487	0.4340
Earnings	1,081,055	1,153,179	1,168,582	1,301,879
Age	21.6935	1.7651	22.0806	1.6709
Sex (0: Female, 1: Male)	0.5291	0.4992	0.4772	0.4997
Area (0: Rural, 1: Urban)	0.5795	0.4937	0.6246	0.4845
Educatio-	2.9703	0.6493	3.0679	0.6578
Job experience (0: Had no experience, 1: Otherwise)	0.4671	0.4990	0.4581	0.4985

Source: BPS-Indonesia, 2021 (Processed)

RESULTS AND DISCUSSION

Table 3 describes the observations used in the research based on participation status in the *Program Kartu Prakerja*. Out of the total observed individuals, 26.18% received intervention in the form of the program, while 73.82% of individuals had registered for the program but did not receive the same treatment. The observations represented different groups in terms of gender and geographical location. Non-participants in the program comprised 52.91% males and 47.09% females, with 57.95% located in urban areas and 42.05% in rural areas. On average, non-participants' highest level of education was at the high school level or equivalent, and 46.71% of observations had no prior work experience.

On the other hand, program participants comprised 49.92% males, and most resided in urban areas. Program participants also had, on average, a high school level of education or equivalent, and around 45.81% had no prior work experience. Additionally, the percentage of observations that were program participants had a slightly lower average probability of retaining employment, at 74.87%, compared to non-participants, which reached 78.98%. However, despite the lower probability of retaining employment, program participants tended to have higher earnings, with an average of around IDR. 1,168,582 per month, compared to the average monthly earnings of non-participants at IDR. 1,081,055.

The study aims to assess how a policy affects job retention and earnings of young participants. To achieve this objective, the study will conduct a comparative analysis between a group of participants and a group of non-participants using the PSM method. This approach will consider various traits from both groups, such as age, gender, area of residence, education level, and previous work experience, and ensure they are comparable. The primary focus of the PSM method is to select similar covariates in both groups and then compare participant groups receiving treatment with control groups with comparable characteristics, which provides more accurate estimates closer to the parameters (Khandker et al., 2009).

The common support, the number of observation units that overlap in the range of propensity scores, is used to determine the number of observations that can be compared. Propensity score estimates are based on the likelihood of a subject being part of the treatment group based on specific characteristics. In this study, propensity score estimation is conducted using probit regression. The distribution of propensity scores shows that the treatment and control groups have an overlapping range, as depicted in Figure 1. The overlap between the distribution of the treatment group and comparison groups is also reasonable. This indicates that there is a strong common support across all covariates used in the participation in the intervention. Based on this common support, the treatment group consists of 943 individuals and the comparison group consists of 2,659 individuals. These individuals can be used for inference analysis.

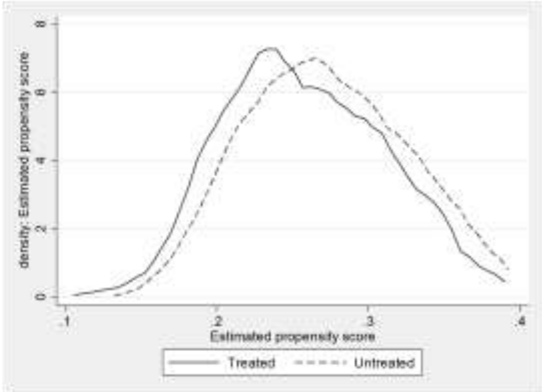

Figure 1. Common Support
Source: BPS-Indonesia, 2021 (Processed)

The study utilizes nearest neighbour (NN) matching, which pairs individuals from the treatment and control groups based on their nearest propensity scores. This method ensures the comparability of propensity scores between the groups being compared. In this study, the size of the "nearest neighbour" group is set to 5. By matching individuals based on their nearest propensity scores, the study aims to create balanced and comparable groups in terms of their propensity to receive treatment, effectively controlling for the differences between the propensity scores of the two groups.

Table 4. The t-test results

Variable	**Sample**	***t*-test**	
		t	**p > |t|**
Age	Unmatched	5.87	0.000
	Matched	0.31	0.759
Sex	Unmatched	-2.74	0.006
	Matched	0.05	0.957
Area	Unmatched	2.42	0.016
	Matched	0.35	0.729
Education	Unmatched	3.95	0.000
	Matched	-1.10	0.270
Job Experience	Unmatched	-0.47	0.635
	Matched	-0.01	0.993

Source: BPS-Indonesia, 2021 (Processed)

After the matching process, a balancing test is used to evaluate the success of the matching method in reducing selection bias. In this study, a paired t-test is used on each covariate variable after the matching process to ensure that the treatment and comparison groups are not significantly different based on the covariate variables used. As per the paired t-test results in Table 4, the study found no statistically significant difference between the treatment and control groups in any covariate variables. This indicates that the treatment and control groups were comparable in terms of their baseline characteristics. The study's matching process significantly reduced average selection bias from 11.8% to 1.6%, as shown in Figure 2. This demonstrates that the matching process successfully made the treatment and control groups more similar in observed characteristics.

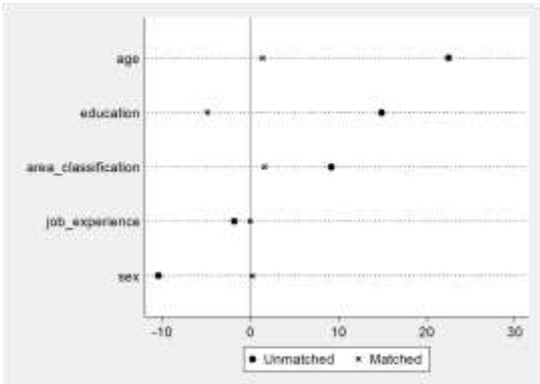

Figure 2. Bias Percentage Comparison
Source: BPS-Indonesia, 2021 (Processed)

The PSM method reveals the Average Treatment Effect on the Treated (ATT) value, which is the difference between the average outcome values of the treatment and comparison groups. In this study, ATT represents the estimated impact of the program on the probability of job retention and earnings for participants. To further ensure the accuracy of the NN (5) matching estimation results, they will be compared with other matching methods, such as radius (0.1) and kernel. This comparison will help validate the reliability of the PSM method used in this research and provide additional insights into the program's impact on the targeted group.

Table 5. The PSM analysis results

Metode	Mean of Matched Treated	Mean of Matched Controls	ATT	t-stat
Probability of job retention				
NN (5) ties	0.7487	0.8002	-0.0515	-3.06
Radius (0,1)	0.7487	0.7917	-0.0430	-2.65
Kernel	0.7487	0.7934	-0.0447	-2.74
Earnings				
NN (5) ties	1,168,582	1,106,307	62,275	1.26
Radius (0,1)	1,168,582	1,097,116	71,465	1.48
Kernel	1,168,582	1,106,345	62,237	1.29

Source: BPS-Indonesia, 2021 (Processed)

Table 5 summarizes the program's effectiveness on the probability of job retention and earnings for young workers. Using three matching methods—NN with five ties, Radius with a 0.1 calliper, and Kernel matching—, the study found a negative effect on job retention. Specifically, the treated group had a lower probability of job retention by 5.15 percentage points (NN), 4.30 percentage points (Radius), and 4.47 percentage points (Kernel). In terms of earnings, the treated group exhibited higher average earnings compared to the control group by IDR 62,275 (NN), IDR 71,465 (Radius), and IDR 62,237 (Kernel). However, these differences were not statistically significant. These results are consistent with other studies evaluating ALMPs in different countries, as the programs do not have statistically significant positive impacts on young labor forces (Card et al., 2018; McKenzie, 2017; Rotar, 2021).

The results imply that the program may have adversely affected the ability of young participants to maintain their jobs, suggesting that some participants left their previous jobs in an attempt to find new ones. Another finding indicates that the program positively affected earnings; however, this impact was not statistically significant. These findings emphasize the program's potential as a strategic intervention to enhance labor market functionality, yet optimization is essential for achieving more substantial outcomes.

Therefore, improvements in the program's management, particularly in selecting beneficiaries, are essential for making the program more inclusive and targeted. Moreover, the training content requires adjustment. The research results indicate that the program's scheme and content provided in 2021 could not increase the probability of job retention and earnings for program participants consisting of young workers. The program's effectiveness can increase if the program and training content selection are designed according to the needs of specific groups, meaning that different groups may have different content. Card et al. (2018) noted that the same program applied to different groups may yield different significant effects.

Furthermore, integrating the Kartu Prakerja Program with other forms of ALMPs could offer comprehensive support to those impacted by employment challenges. For the supply side, incoIDRorating on-the-job training and job search assistance alongside demand-side approaches like wage subsidies can create a robust framework for employment support (Escudero, 2018). Reflecting on international examples, Indonesia could draw valuable insights. Australia's JobTrainer Fund is a successful model that provides free or low-cost training and wage subsidies for apprenticeships. This initiative supports employment and aids in the skill-matching process for workers who have been displaced (APEC, 2021). Another noteworthy program is Italy's PIPOL, an integrative approach to active labor policies. Off-the-job training alone did not have a significant impact, but it had a positive net effect when combined with on-the-job training. This reflects that young people in the job market may have strong theoretical knowledge but lack work experience and work-related skills (Pastore, 2015; Pastore & Pompili, 2020). Adopting strategies similar to those used as policy options could benefit Indonesia.

CONCLUSION

This study emphasizes the need to analyze the impact of intervention policies in the labor market on the young age group who are already employed. Using the August 2021 Sakernas data, this study employs the PSM method to compare the treatment group receiving the program with the control group not receiving the intervention. Our results showed that the program had a negative impact on the ability of young participants to maintain their jobs, which suggests that some participants left their current jobs in an attempt to find new ones. We also found that the program positively affected earnings, but this impact was not statistically significant. These findings highlight the program's potential as a strategic intervention to enhance labor market functionality, but further optimization is needed to achieve more significant outcomes.

Several research recommendations are proposed to enhance the program's effectiveness. First, program management aspects, especially beneficiary selection management, require improvement to make the program more inclusive and targeted. Second, adjusting the training content according to each group's needs is essential to improve program effectiveness. Furthermore, relevant support programs such as on-the-job training, job search assistance, counselling, and monitoring are necessary.

However, this study has some limitations that need to be considered. The Sakernas data used in the study did not provide information about the exact timing when observation units received the treatment. Additionally, the study uses cross-sectional data, which does not allow for analysis of changes over time. Future research should consider using more detailed primary data and conducting analyses using a panel approach to understand the program's impact over time better.

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