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DOES TRAINING WITH INCENTIVES WORK? IMPACT EVALUATION OF INDONESIA'S PRE-EMPLOYMENT CARD

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Abstract

The government's pre-employment card scheme aims to enhance the capabilities of Indonesian workers, making them more competitive and efficient. Simultaneously, it serves as a safety net to alleviate the effects of the COVID-19 crisis. This study seeks to evaluate how the pre-employment card program influences the time taken to prepare for employment and improve skills. The focus is on whether this initiative can decrease the waiting period for job seekers and enhance the skills of the participants. The research utilises the Propensity Score Matching technique and data from the Survei Kerja Nasional in February 2021. The findings suggest that the pre-employment program has a notable positive impact on the skills development of those involved, by 0.08199%. While skill enhancement is evident, the scheme has not led to a reduction in the time it takes for individuals to secure employment. The effectiveness of the program could be enhanced through the implementation of additional policies, including the improvement of labour market information systems and the provision of active employment support services by the government.

Keywords: *Pre-Employment Card, Propensity Score Matching, Impact Evaluation, Job Search Duration, Skill Improvement*

INTRODUCTION

Unemployment is an important indicator of a country's economic performance (Ibarrarán et al., 2015). Unemployment rates reflect imbalances in the labor market, both in terms of supply and demand for labor. These imbalances can be caused by a variety of factors, including structural changes in the economy, technological advancements that reduce the need for labor, and ineffective labor policies that fail to create new jobs (Pramana & Yusa, 2024).

The unemployment rate can be seen as a dual challenge for policymakers. A high unemployment rate indicates that some individuals are unable to support themselves. On the other hand, if the unemployment rate is too low, it indicates an excess demand for labor, potentially driving up wages and inflation, an effect commonly described by the Phillips Curve. In addition, long term unemployment can hinder economic growth, reduce people's purchasing power, and increase the social burden on the government through various

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assistance and subsidy programs. Therefore, understanding the dynamics of unemployment and causes of unemployment is crucial in designing sustainable economic policies.

In Indonesia, the impact of the COVID-19 pandemic further worsened employment conditions. Data from Statistic Indonesia (BPS, 2020) shows that in 2020, 14,28% of the working-age population was affected by COVID-19, which resulted in an additional 2,56 million new unemployed. Thus, the unemployment rate rose from 4,94% in February 2020 to 7,07% in August 2020. On the other hand, significant portion of the unemployment population, aged between 15 and 40 years old. This phenomena reflects the challenges of Indonesia’s demographic bonus, which has not been accompanied by proportional job growth (Novella & Valencia, 2022).

High levels of unemployment are often linked to the labor market systems in place within a country. In response to this issue, nations experiencing high levels of joblessness have been encouraged to implement comprehensive reforms aimed at reducing "labor market rigidities". These rigidities may include generous unemployment benefits, strict employment protection laws, such as high costs associated with firing employees, high minimum wage requirements, wage-setting methods that do not encourage competition, and significant tax discrepancies. These factors can impact a government's ability to effectively balance economic policies, particularly when it comes to managing inflation rates and employment levels. There are various reasons contributing to the unemployment rate in Indonesia, including a lack of necessary skills in the workforce, mismatch between the skills individuals possess and the available job opportunities, and a disproportionate distribution of the population across different regions (Chakravarty et al., 2019; Lichter & Schiprowski, 2021; Novella & Valencia, 2022).

The country’s relatively low labor competitiveness also plays a role. According to the IMD World Talent Ranking reports that Indonesian workforce competitiveness ranked 40th out of 63 countries between 2017 and 2021. Indonesia's competitiveness score declined significantly during this period, which is explained by the country's lack of innovation and human resource development. Furthermore, the COVID-19 pandemic in 2020 deepened these challenges, causing many jobs to be lost and further complicating the Indonesian labor market.

Young workers is the largest portion of the population in developing countries, including Indonesia. This situation presents both a significant opportunity and a challenge: a challenge for the government to expand employment opportunities and increase youth income, and an opportunity to advance national development (Fox & Kaul, 2018). In Indonesia, the labor force grew by 18,5% in 2020 compared to 2010. However, job creation has lagged behind the growth of the working-age population. Youth aged 15 to 24 years have consistently contributed to around 30% of the total open unemployment in Indonesia from 2015 to 2021.

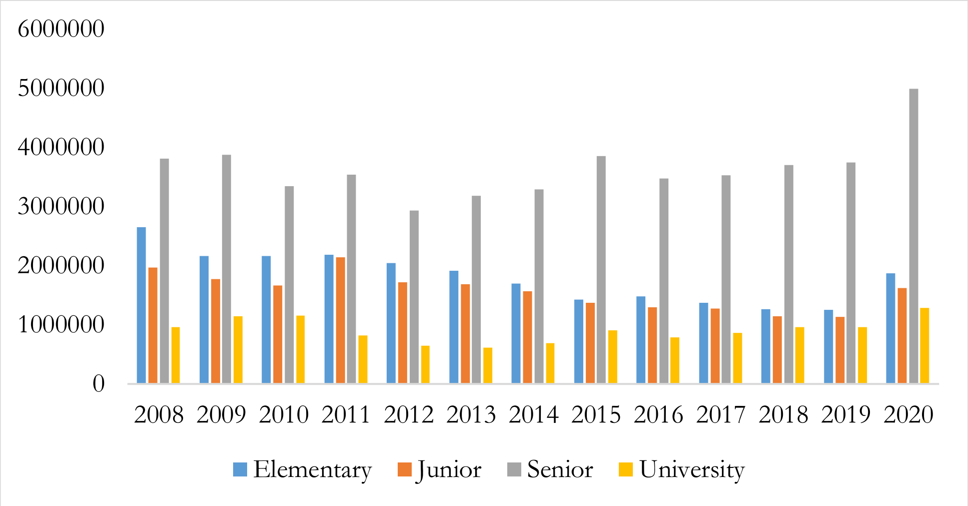

Figure 1. Unemployment by Education Level
Source: Statistic Indonesia, 2021

Unemployment in Indonesia is not only concentrated among young workers but also varies by education level. Figure 1 shows that individuals with upper secondary and higher education levels represent the largest share of the unemployed and this trend has been increasing annually. Unemployment among university graduates has also shown a steady rise over the years.

In unemployment cases, budget constraints among job seekers significantly reduce consumption (Bahk, 2021). To mitigate the economic impact of the pandemic in Indonesia, the government launched a Social Safety Net (Jaring Pengaman Sosial) program in 2020. One initiative under this program to address the labor market's challenges is the Pre-Employment Card (Kartu Prakerja). Pre-Employment Card is designed for skills training but was later adapted into a semi-social assistance program targeting the labor force. The Pre-Employment Card program provides not only financial incentives to recipients but also offers training to support the development of skills, competitiveness, and competencies, thereby enhancing job readiness.

Social security or pre-employment cards schemes play an important role in enhancing the labor market's performance. This programs offer two primary benefits: first, they protect workers from income loss and enable them to maintain consumption levels after job loss; second, they help prevent the emergence of new poverty and promote income equity (Hijzen & Salvatori, 2020). The Pre-Employment programs use as a semi-social support program targeting workers affected by the pandemic, addressing both labor market and broader economic challenges. The Pre-Employment program can be viewed as a hybrid model which offering not just financial relief but also skill-building to enhance labor force quality.

During the first year of its implementation, several adjustments were made to the Pre-Employment Card program. Initially, the program's budget was set at 20 trillion rupiah but was increased to 30 trillion rupiah in the second half of 2020. The duration of incentives was also extended from three months to four months, and additional legislative regulations were introduced to regulate the program effectively.

Katz and Meyer (1990) found that the likelihood of finding employment more than doubles after social security expire, with some workers accepting jobs that pay less than their previous roles. However, social security may also influence worker behavior, creating a moral hazard effect where beneficiaries remain unemployed longer (Goller et al., 2025; Lichter & Schiprowski, 2021; Rotar & Krsnik, 2020; Shen, 2020). Combining social security with training programs, however, can enhance beneficiaries' skills (Beam & Quimbo, 2021; Ibarrarán et al., 2015). This study aims to evaluate the impact of the Pre-Employment Card program on the duration of job preparation and the enhancement of workers' competencies, particularly as measured by their use of information technology (IT) in the workplace.

LITERATURE REVIEW

In the context of workforce development, job search duration, and social security, several studies provide valuable perspectives that relevant to the design and impact of Indonesia's Pre-Employment Card Program *(Kartu Prakerja)*. This program is a workforce competency development initiative aimed at job seekers, workers who have been laid off, and individuals needing skills enhancement. It combines training with financial incentives to increase productivity, competitiveness, and entrepreneurial capabilities of the Indonesian labor force.

The design of the *Kartu Prakerja* shares similarities with social security programs in the other countries that integrate both cash transfers and training components. One notable example is the Youth Opportunities Program (YOP) in Northern Uganda, which started in 2006. It is a continuation of the Northern Ugandan Social Action Fund (NUSAF). YOP is an unconditional cash transfer program combined with skills training, aimed at thousands of

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young workers aged 16 to 35. The types of skills training in this program included vocational training, equipment handling, and initial business costs. The main goals of YOP is to increase income and employment opportunities for youth, promote community reconciliation, and reduce conflict. Evaluation showed that YOP significantly increased youth income and reduced unemployment, especially among male participants (Blattman & Ralston, 2015).

In Germany, Lichter and Schiprowski (2021) employed a Difference-in-Differences approach to analyze the impact of extending Unemployment Insurance (UI) benefits from 12 to 15 months for older workers. Their study found that longer benefit periods led to a significant increase in the average duration of unemployment, indicating a behavioral response to more generous support systems. Similarly, Shen (2020) examined the relationship between unemployment benefits, job search duration, and post-unemployment wages in the U.S. using data from NLS79 and NLS97. The study found that higher benefits prolonged job searches, though they did not significantly affect post-unemployment wages, even during different recession periods. This implies a trade-off between financial security during unemployment and the speed of labor market reintegration.

Rotar and Krsnik (2020), analyzed panel data from EU-28 countries from 2006 to 2018 to examine how macroeconomic factors and social policies influence unemployment dynamics. They found that stronger social policies can shorten unemployment duration, while unstable economic conditions tend to lengthen it. This highlight is aligning program design with economic conditions and labor market realities. Collectively, these studies show that social security programs combining cash assitance and training can improve skill levels and job matching. However, their effect on job search duration is different often influenced by the policy structure and macroeconomic conditions.

RESEARCH METHOD

This study uses secondary data from the February 2021 National Labor Force Survey (SAKERNAS). Java was selected as the sample of this study because 53.89% of Pre-Employment Card recipients located in this Island. The study focuses on the first period of the program's implementation in 2020, covering batches 1 through 11.

To evaluate the program's impact on job preparation duration and skill development, the Propensity Score Matching (PSM) method was applied. The PSM model was chosen to minimize potential selection bias. This model allows to create a valid comparison group from non-recipients with similar observable characteristics. This comparison group, generated from the PSM model, serves as a reliable baseline to measure the program's effects on the

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treatment group. After constructing a valid comparison, the difference between the two groups is the receipt of the Pre-Employment Card (Caliendo & Kopeining, 2008).

This study evaluates two main outcomes. First, the duration of preparing for work, which is measured by how long it takes workers to look for work or prepare for a business. Second, skill development measured by the use of information technology (IT) in the workplace.

The difference in the outcome between the group that received pre-employment and those that did not receive pre-employment was measured by the formula:

$$Yi = Di\ Y1i + (1 - Di)\ Y0i$$

In the above equation, Di represents a dummy variable indicating whether the worker receives benefits from the Pre-Employment Card program, where 1 denotes receiving the benefits and 0 otherwise. Yi denotes the outcome variable, which includes the duration of preparing for work and skill improvement. Y1i refers to the potential outcome for individual i when receiving the benefits, while Y0i represents the potential outcome for the same individual when not receiving the benefits.

Thus, the impact of an individual receiving the intervention from the Pre-Employment Card program can be formulated as follows:

$$\tau = Y1i - Y0i$$

Since counterfactual outcomes cannot be directly observed, namely a condition where the intervention recipient group cannot simultaneously receive and do not receive an intervention. The study employs the Average Treatment Effect on the Treated (ATET) to estimate the program's impact by comparing the actual outcomes of recipients $E(Y1i \mid Di = 1)$ with the counterfactual outcomes of non-recipients $E(Y0i \mid Di = 0)$. The Propensity Score Matching (PSM) method ensures valid comparison by addressing selection bias, under the assumptions of Conditional Independence and Common Support (Caliendo & Kopeinig, 2008).

Variables

Outcome Variables

The outcome variables used in this study to measure the impact of the Pre-Employment Card Program include the waiting time or duration job seekers spend preparing for employment and competency improvement, which is measured through the use of information technology (IT).

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Variable of Interest

The main explanatory variable in this study is the status of receiving the Pre-Employment Card Program. This is treated as a dummy variable, where individuals in the labor force who received the program are coded as 1, and those who did not are coded as 0. This data is derived from the February 2021 Sakernas questionnaire, based on the question: "Did you pass the selection for the Pre-Employment Card Program?".

Control Variables

The vector of labor force and household characteristic variables, also referred to as control variables, is used to identify factors that influence whether a member of the labor force receives the benefits of the Pre-Employment Card Program. These control variables also serve to equalize characteristics between individuals in the treatment and control groups, ensuring more reliable comparisons.

These characteristics are used to group individuals with similar profiles who received or did not receive the program. Control variables include both individual personal attributes and family background characteristics.

Table 1. Operational Definition of Variables

Variable	Description
Outcome Variables	
Job Search Duration	Duration of job search or time spent preparing to start a business, measured in month
IT	Use of IT for work activities; 1 = uses IT, 0 = does not use
Variable of Interest	
Pre-Employment Card	Dummy variable indicating program participation; 1 = received, 0 = not received
Control Variables	
Gender	0 = male, 1 = female
Education Level	Level of educational participation
Age	Age of the individual in the labor force
Marital Status	1 = married, 0 = not married
Layoff Status	Job status before receiving the program (laid off or not)
Industry Sector	Type of employment sector (informal/formal)
Household Size	Number of household members
Labor Force Status	1 = unemployed, 2 = underemployed, 3 = fully employed

RESULTS AND DISCUSSIONS

Research Results

Descriptive statistics

This study uses secondary data from national labor force survey conducted in February 2021. The total sample includes 2.854 individuals who registered for the Pre-Employment Card Program. 561 individuals (19,66%) received the pre-employment program, and 2.293 individuals (80,34%) did not receive the pre-employment program.

Table 2 shows the descriptive statistic this research. The longest duration of job preparation in the treatment group was 14 months, while in the control group it was 98 months. The use of information technology (IT) for work-related activities was reported by 54% of the control group and 47% of the treatment group. Most applicants for the Pre-Employment Card program were male, 58,90%. The majority of both applicants and recipients had completed senior high school (around 60%), followed by higher education levels at around 18%. Those with no formal education made up the smallest group, 0.5% of the sample.

In terms of marital status, 57% of participants were married. A total of 711 informal workers applied for the program, with 22% of them received the Pre-Employment Card benefits. Among the 521 laid-off workers, about 30% became beneficiaries. The remaining 70% included people who were still employed, looking for work, or starting a business.

Among recipients, 42% were full-time workers. In the unemployed category, 941 individuals registered for the program, of whom 18,81% received the program. On average, across the three labor force status categories, 18% of applicants became the Pre-Employment Card beneficiaries.

Table 2. Descriptive Statistics

Variable	Category	Treatment			Control		
		Total	%	Mean	Total	%	Mean
Outcome Variables							
Duration on preparing work	Minimal	0		0,74688	0		0,62669
	Maximal	14			98		
IT for work	Yes	308	11		1.060	37	
	No	253	9		1.233	43	
Control Variable							
Age	Minimal	18		30,69			
	Maximal	69			18		30,97
Gender	Male	337	12		71	47	
	Female	224	8		1.344	33	
Education	No formal education	3	-		949	0	

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Variable	Category	Treatment			Control		
		Total	%	Mean	Total	%	Mean
	Primary school	25	1		14	5	
	Junior school	58	2		137	12	
	Senior school	354	12		341	49	
	University	121	4		1.389	14	
Marital status	Married	323	11		412	46	
	Single	238	8		1.304	35	
Layoffs	Layoffs	153	5		989	13	
	No layoffs	408	14		368	67	
Type of work	Informal	159	6		1.925	19	
	Formal	402	14		552	61	
Labor force status	Unemployed	148	5		1.741	23	
	Underemployed	177	6		660	27	
	Full working	236	8		764	30	
N		561			2.293		

Source: Sakernas, 2021

Estimation Result of Propensity Score Matching

Logit model estimation

The probability of receiving the Pre-Employment Card based on observed individual characteristics can be seen in the logit model. Table 3 shows that 4 of the 7 variables used in this study significantly influence the probability of a worker receiving this program. The results of the logit model show that age, gender, and marital status do not significantly affect the probability of receiving this program.

Other variables, such as education, employment status, workforce status, and type of work significantly influence the probability of a workforce receiving a pre-employment card program. Education level has a significant effect on a person's probability of receiving pre-employment. Consistent with the results of research conducted by Kluve et al. (2019) say that the characteristics of individuals participating in youth employment programs are important because by knowing the profile of program recipients, program features and design can be adjusted. Information on beneficiary profiles such as education level can be used to provide services that best suit the constraints faced by participants.

Employment status (layoffs) also has a significant effect on the probability of an individual receiving pre-employment. Pre-employment program was originally aimed for the unemployed and job seekers, so they can improve their abilities to find or prepare for work through training skills in pre-employment card. Consistent with the results of research conducted by Ibarraran et al. (2015) a similar program in the Dominican Republic was able to reduce unemployment and improve the skills of program recipients. Individuals who have experienced layoffs are more likely to become program recipients, as training tends to more effective for vulnerable populations (Doerr & Novella, 2024).

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Table 3. Logit Model

Variable	Coefficient	Standard Error
Age	-0,00648	0,00604
Gender	0,04255	0,09963
Level of education	0,22614***	0,06619
Marital status	0,14967	0,11496
Labor force status	0.10917*	0,05720
Type of work	0,26417**	0,11124
Layoffs	0,44921***	0,11032
Constanta	-2,61262	0,35812

Notes:

The dependent variable is pre-employment with a value of 1 if it receives pre-employment and 0 if otherwise

*significant at 10%, **significant at 5%, ***significant at 1%

Source: Sakernas, 2021

Matching algorithm

Matching algorithm is a method used to obtain the best estimates for assessing the average treatment effect. The matching algorithms are categorized into four main types: Nearest Neighbor (NN), Caliper and Radius, Stratification and Interval, and Kernel and Local Linear Weighting. Figure 2 shows that the distribution of propensity scores in the treatment group is higher than in the control group. Nearest Neighbor (NN) can be used in this study as the distribution of the propensity score between the treatment group and the control group has a similarity in each block.

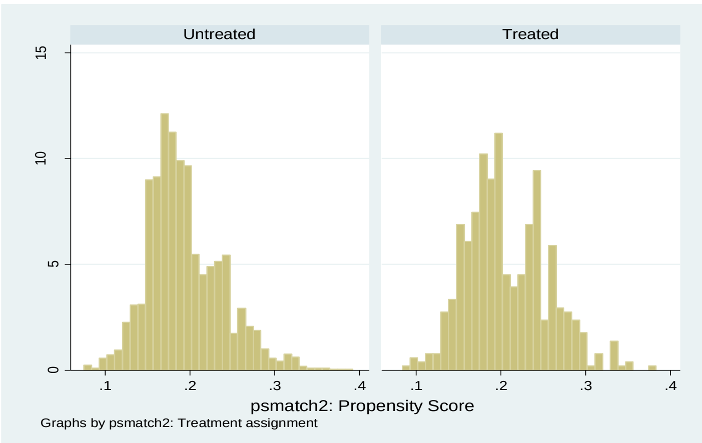

Figure 2. Comparison of the distribution of propensity scores before matching
Source: Sakernas, 2021

Common support

Common support step to ensures that treatment and control group are adequately matched. Figure 3 shows an area of overlap between the density distribution of the propensity scores in both groups. This overlap indicates that the observed characteristics in

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the treatment group also appear in the control group, thereby satisfying the common support condition and both groups can be reasonably compared (Caliendo & Kopeinig, 2008).

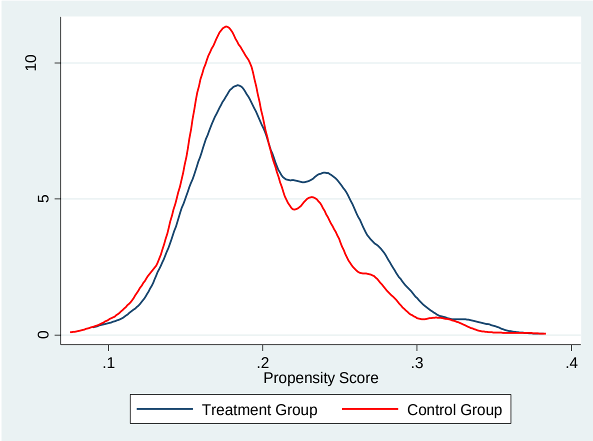

Figure 3. Distribution and common support propensity score
Source: Sakernas, 2021

Matching quality

The matching process is considered successful if the standard bias test shows a decrease in the standard bias after matching. Matching quality is assessed using standardized bias before and after matching. Table 4 shows that there is a decrease in standard bias after matching all variables. There is no standard indicator of matching quality, but a decrease below 3% or 5% is considered sufficient (Caliendo & Kopeinig, 2008).

Table 4. Standard bias with NN matching without replacement

Variable	% bias before matching	% bias after matching	% bias reduction
Preparation time	5	12,1	-141,7
IT	17,4	16,1	7,5
Age	-2,9	13,9	-383,8
Gender	3	0,4	87,8
Education	15	-1,9	87,5
Marital status	1,4	-2,2	-51,3
Labor force status	7	-0,6	91
Layoffs	18,7	3,4	81,9
Type of work	9,7	5,7	41,5

Source: Sakernas, 2021

The t-test is used to check the average similarity before and after matching. After matching, all variables showed the average similarity between the treatment group and the control group, shown with the p-value of the t-test was greater than the p-value at 5%. Some of outcome variable, the average of the variables differs between the treatment group and the control group, because the outcome variable will be seen as the impact of the treatment. In conclusion, the matching quality check by t-test showed good results.

Sensitivity analysis

Sensitivity analysis is conducted to assess whether there is hidden bias caused by unobserved variables that significantly affect the model's outcomes. Table 5 shows the impact of having a pre-employment card on some of the outcomes. This test can be said that research is sensitive to selection bias because the average gamma value is 1,2 and has an insignificant p-value at the 0,05 level (Rosenbaum, 2005).

Table 5. Sensitivity analysis

Outcome	Sensitivity analysis
Duration on preparing work	Sensitive
IT at work	Sensitive

Source: Sakernas, 2021

Discussion

The impact of pre-employment on the outcome variable of the duration of preparing for work is presented in Table 6. The estimation results using the Nearest Neighbor (NN) without replacement indicate that the program increases the time individuals spend preparing for employment. Specifically, recipients of the Pre-Employment Card took, on average, 0,14 months longer to prepare for work compared to non-recipients.

This finding aligns with previous studies. First, research by Litcher and Amelia (2021) in Germany found that the longer duration of unemployment benefit led to longer unemployed durations. Second, Shen (2020) in the United States showed that higher unemployment benefits associated with longer duration of job search. Furthermore, research by Rotar and Krsnik (2020) found that unstable economic conditions influence both unemployment benefits and the duration of looking for work. Additionally, Cerque et al. (2020) reported similar dynamics in related contexts.

The design of the Pre-Employment Card provides further explanation for these outcomes. Pre-Employment recipients are required to participate in a training programs to receive incentives and obtain proficiency certificates. The duration of the training program varies depends on the type and number of training selected by the pre-employment recipients. Pre-employment recipients must purchase their first training within a maximum of 30 days after qualifying as a pre-employment card recipient, otherwise, participation will be revoked. The duration of training program can also affect the duration of employment for pre-employees. In addition, there is a difference in the length of time looking for work between new graduates and new layoffs during February 2020-February 2021. On average,

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new graduates get job faster than new layoffs, new graduates tracked in the 2021 Sakernas survey wait for work for 0.833 months and new layoffs wait worked longer for 2,166 months.

Labor market imbalances also play a role. In 2020. The ratio of registered job seekers to the number of job vacancies at 40.52%, lower than in 2019 which was 53.45% (Statistic Indonesia, 2020). Based on the increase in reported vacancies in 2020, reported vacancies increased from 265,577 in 2019 to 3,481,241. However, the increase in reported vacancies is still smaller than the increase in registered job seekers because the number of job seekers increased 17 times compared to 2019 from 496,915 people looking for work to 8,592,255.

Table 6. Impact estimation of the Pre-Employment Program

Outcome	Matching Method	Impact	Standard Error
Duration on preparing work	NN without replacement	0,14081	0,11170
	NN with replacement	0,29055*	0,11209
IT at work	NN without replacement	0,08199*	0,02977
	NN with replacement	0,08021*	0,03614

*Statistically significant at p=0.10

Source: Sakernas, 2021

The program also has a positive and statistically significant effect on skill development. Skill development measured by the use of IT at work. The findings indicate that Pre-Employment Card recipients were 0,08199% more likely to use IT at work compared to non-recipients, suggesting a meaningful improvement in digital competence.

Indonesia's Pre-Employment Card program is similar to social security programs combined with training in some countries such as Northern Uganda, Argentina, Bolivia, and the Dominican Republic. Recipients of this programs in these countries have been shown to experience an increase in skills, consistent with the findings of this study on improved skills of pre-employment recipients. The Juventud y Empleo program in the Dominican Republic, which had similar program intervention requirements and formats to the pre-employment card program, was able to improve the skills and increase the income of the beneficiaries, but the program could reduce unemployment in the long-term, not short-term (Ibarrarán et al., 2015).

Social security and training are one of the supply-side interventions in the labor market that can reduce unemployment, especially in the long term and countries with high levels of informality (Fox & Kaul, 2018; Goller et al., 2025; Novella & Valencia, 2022). Unemployment rates fell after the training interventions because the special training and skills received by program recipients may increase motivation, willingness to work and work

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readiness (Alzúa et al., 2021). Second, training that is adjusted to the needs of the labor market and formal jobs can affect job search duration (Beam & Quimbo, 2021). Another effect of the pre-employment card considered part of social assistance has been described as successful. Pre-employment cards can protect workers from the risk of losing income. 52% of pre-employment recipients take advantage of the incentives to fulfill their daily needs. As many as 21.97% of pre-employment recipients take advantage of the incentives as business capital according to one of the pre-employment card purposes.

A semi-social assistance policy system that targets the labor market is very important as it can replace lost income caused by unemployment (Marinescu et al., 2021; McIntosh & Zeitlin, 2022). However, programs such as unemployment benefits or pre-employment cards still have the disadvantage of not encouraging active job behaviour. Financial incentives tied to unemployment or upskilling can reduce short-term job search intensity (Marinescu et al., 2021).

The effectiveness of unemployment benefits is highly depend on the characteristics of the social policy system, labor market conditions, labor supply, and demand characteristics (Doerr & Novella, 2024; McIntosh & Zeitlin, 2022; Rotar & Krsnik, 2020). The Pre-Employment Cards scheme appears to have limited impact on labor market due to unstable economic and labor markets conditions. For greater impact, this program should have complementary policy by providing active employment services and adopt a demand-driven design, align training components with real-world labor market needs and employer demand.

CONCLUSION

Several conclusions can be drawn from the findings on the estimated impact of the pre-employment card on the job search duration and skill development. First, the pre-employment cards do not significantly reduce the duration of job preparation. Second, this program has significantly impact on skill improvement. Lastly, the pre-employment card serves as an effective forms of semi-social security to support the workforce. Despite this program gives positive outcomes, the program's ability to shorten job search duration remains limited. This program will more effective if government make complementary policy, such as improving labor market information systems and providing active employment services.

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E-ISSN: 2961-8428

REFERENCES

Alzúa, M. L., Batbekh, S., Batchuluun, A., Dalkhjav, B., & Galdo, J. (2021). Demand-Driven Youth Training Programs: Experimental Evidence from Mongolia. *World Bank Economic Review*, *35*(3), 720–744. https://doi.org/10.1093/wber/lhaa013

Bahk, S. A. (2021). *Do Greater Unemployment Benefits Lead to Better Matches ? Evidence from Emergency Unemployment Compensation Programs* (EQINEQ Working Paper 2021-59). http://www.ecineq.org/wp-content/uploads/papers_EcineqLSE/EcineqLSE-59.pdf

Beam, E., & Quimbo, S. (2021). The Impact of Short-Term Employment for Low-Income Youth: Experimental Evidence from the Philippines. *SSRN Electronic Journal*, *14661*. https://doi.org/10.2139/ssrn.3913022

Blattman, C., & Ralston, L. (2015). Generating employment in poor and fragile states: Evidence from labor market and entrepreneurship programs. *Available at SSRN 2622220*. https://www.peiglobal.org/themes/custom/pei_b5/kc_files/Blattman, et.al. 2015.pdf

BPS. (2020). *Tingkat Pengangguran Terbuka (TPT) sebesar 7,07 persen*. https://www.bps.go.id/id/pressrelease/2020/11/05/1673/-revisi-per-18-02-2021--agustus-2020--tingkat-pengangguran-terbuka--tpt--sebesar-7-07-persen.html

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys*, *22*(1), 31–72. https://doi.org/10.1201/b17084-30

Cerqua, A., Urwin, P., Thomson, D., & Bibby, D. (2020). Evaluation of education and training impacts for the unemployed: Challenges of new data. *Labour Economics*, *67*(November 2017). https://doi.org/10.1016/j.labeco.2020.101907

Chakravarty, S., Lundberg, M., Nikolov, P., & Zenker, J. (2019). Vocational training programs and youth labor market outcomes: Evidence from Nepal. *Journal of Development Economics*, *136*, 71–110. https://doi.org/10.1016/j.jdeveco.2018.09.002

Doerr, A., & Novella, R. (2024). The long-term effects of job training on labor market and skills outcomes in Chile. *Labour Economics*, *91*(August), 102619. https://doi.org/10.1016/j.labeco.2024.102619

Fox, L., & Kaul, U. (2018). The Evidence Is In: How Should Youth Employment Programs In Low-Income Countries Be Designed? *The Evidence Is In: How Should Youth Employment Programs In Low-Income Countries Be Designed?* https://doi.org/10.1596/1813-9450-8500

Goller, D., Lechner, M., Pongratz, T., & Wolff, J. (2025). Active labor market policies for the long-term unemployed: New evidence from causal machine learning. *Labour Economics*, *94*(April), 102729. https://doi.org/10.1016/j.labeco.2025.102729

Hijzen, A., & Salvatori, A. (2020). The design of unemployment benefits schedules over the unemployment spell: The case of Belgium. *Working Paper OECD*.

Ibarrarán, P., Ripani, L., & Ibarrarán, P. (2015). *of a Youth Training Program Experimental Evidence on the Long-Term Impacts of a Youth Training Program*. *9136*.

Kluve, J., Puerto, S., Robalino, D., Romero, J. M., Rother, F., Stöterau, J., Weidenkaff, F., & Witte, M. (2019). Do youth employment programs improve labor market outcomes? A quantitative review. *World Development*, *114*, 237–253. https://doi.org/10.1016/j.worlddev.2018.10.004

Lawrence F. Katz and Bruce D. Meyer. (1990). Unemployment Insurance , Recall Expectations , and Unemployment Outcomes of individual unemployment spell dura- search framework in wh. *The Quarterly Journal of Economics*, *105*(4), 973–1002.

Lichter, A., & Schiprowski, A. (2021). Benefit duration, job search behavior and re-employment. *Journal of Public Economics*, *193*, 104326. https://doi.org/10.1016/j.jpubeco.2020.104326

Marinescu, I., Skandalis, D., & Zhao, D. (2021). The impact of the Federal Pandemic Unemployment Compensation on job search and vacancy creation. *Journal of Public Economics*, *200*, 104471. https://doi.org/10.1016/j.jpubeco.2021.104471

McIntosh, C., & Zeitlin, A. (2022). Using household grants to benchmark the cost effectiveness of a USAID workforce readiness program. *Journal of Development Economics*, *157*. https://doi.org/10.1016/j.jdeveco.2022.102875

Novella, R., & Valencia, H. (2022). Active Labor Market Policies in a Context of High Informality: The Effect of PAE in Bolivia. *Journal of Development Studies*, *58*(12), 2583–2603. https://doi.org/10.1080/00220388.2022.2120803

Pramana, I. W. B., & Yusa, I. G. (2024). Minimum Wage for Workers in Micro and Small Enterprises: Analysis of Government Regulation Number 36 of 2021. *Policy, Law, Notary And Regulatory Issues*, *3*(3), 418–424. https://doi.org/10.55047/polri.v3i3.1379

Rotar, L. J., & Krsnik, S. (2020). Analysing the relationship between unemployment benefits and unemployment duration. *Society and Economy*, *42*(3), 280–297. https://doi.org/10.1556/204.2020.00009

Shen, R. (2020). The Effect of Unemployment Benefits on Job Search Duration and Post-Unemployment Wage. *Carnegie Mellon University. Thesis*, *Chetty 2008*, 1–20.